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This report develops a framework that recognizes and models uncertainty in all the stages of the infrastructure management process. Special emphasis is given to the integration of errors in data collection with errors in deterioration prediction, since no examples of such an approach are found in the literature. The motivation for a probabilistic impact model that includes the effects of uncertainties in data collection is discussed; and concepts relating to deterministic impact modeling are described. The sources of uncertainty in data collection and on the modeling of impacts are identified. The different approaches available in the infrastructure literature and in other fields for probabilistic modeling are also described. The final stage of the infrastructure maintenance management process, strategy selection, is discussed together with the nature of the uncertainty and probabilistic frameworks found in the literature. Directions for future research, including identification of data collection needs and areas for model development, are identified. <i>Key words:</i>					
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THE ROLE OF UNCERTAINTY IN THE MANAGEMENT OF INFRASTRUCTURE FACILITIES

FINAL REPORT

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January 6, 1988

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Table of Contents

1 INTRODUCTION	1
2 CONCEPTS IN MODELING IMPACTS FOR INFRASTRUCTURE FACILITIES ..	5
3 SOURCES OF ERROR AND RANDOMNESS	9
3.1 SOURCES OF ERROR IN DATA COLLECTION	9
3.2 SOURCES OF ERROR IN MODEL SPECIFICATION	15
3.3 SOURCES OF UNCERTAINTY DUE TO RANDOMNESS IN NATURE	15
4 APPROACHES TO MODELING ERRORS	16
4.1 DATA COLLECTION PROCESS	16
4.2 PROBABILISTIC MODELS OF INFRASTRUCTURE DETERIORATION	26
4.3 PROBABILISTIC AND STATISTICAL IMPACT MODELING	27
4.4 UNCERTAINTIES IN STRATEGY SELECTION	28
5 A FRAMEWORK FOR MODELING UNCERTAINTY	31
5.1 MODELING FRAMEWORKS IN THE LITERATURE	33
5.2 A COMPREHENSIVE APPROACH	42
6 SUMMARY AND DIRECTIONS FOR FUTURE RESEARCH	47
7 REFERENCES	48
8 APPENDIX: EVALUATION OF AUTOMATED INSPECTION SYSTEMS FOR PAVEMENT SURFACE DISTRESS	52

Table of Figures

Figure 1.1 The Infrastructure Management Process	2
Figure 4.1 Schematic Overview of the Data Collection Process	18
Figure 4.2 Example Contingency Table	21
Figure 4.3 Temporal Component of the Greenness Component for Two Different Crops .	21
Figure 4.4 Direct Method Probability Decay Function	23
Figure 5.1 Characterization of Data Collection and Modeling	32
Figure 5.2 The Framework for Decision-Making	36
Figure 5.3 Decision Theoretic Framework	38
Figure 5.4 Discrete Mapping Flow Chart	39

Table of Tables

Table 3.1 Sources of Error	10
Table 4.1 Mapping Error for Various Sampling Techniques	23
Table 4.2 Comparison of Defects Detected From Sketches and Prints	25
Table 5.1 Summary of Equations Modeling the Facility Management Process	46

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1 INTRODUCTION

Estimates of annual expenditures for public infrastructure renewal over the next 25 years vary from \$53 billion [1] to \$159 billion [2]. The extraordinary range in these estimates can be partially attributed to the inherent variability and different methods used for assessing the condition of the facilities and the rehabilitation and repair needs. Nevertheless, the resources for infrastructure repair and renewal are insufficient to satisfy even the most conservative estimates. Efficiently allocating resources to projects requires a thorough understanding of the costs and consequences of neglect, maintenance, rehabilitation and reconstruction. Considerable research has been devoted to deterioration models and the selection of cost effective maintenance and rehabilitation strategies. Balta [3] provides a summary of methods and research for pavements. However, previous research has not consistently included uncertainty in the data, models, and the decision process. The presence of uncertainty is evident in the inability of these models to predict catastrophic failure, in highly variable service lives, in the development of ineffective or inappropriate strategies [4] and in the variability of cost estimates as illustrated by the wide range of needs estimates [1] [2]. This paper develops a comprehensive modeling framework that includes uncertainty in all phases of the infrastructure management process for transportation facilities. The representation of the process used in this paper applies to many different types of infrastructure including roads, pipelines, waterways and rail. This paper develops a general approach to infrastructure management although the concepts are illustrated using elements of transportation infrastructure such as highways, bridges and rail.

Infrastructure management decisions are made on the basis of predictive models that are developed from facility condition data collected in the field. Figure 1.1 represents the process in the steady state when the facility is mature and sufficient data is available to allow model estimation. The process is depicted as a dynamic system with feedback to facilitate the updating of models as experience is gained with strategies that have been implemented. As experience is gained, it is possible that the objectives which are evaluated might themselves change and

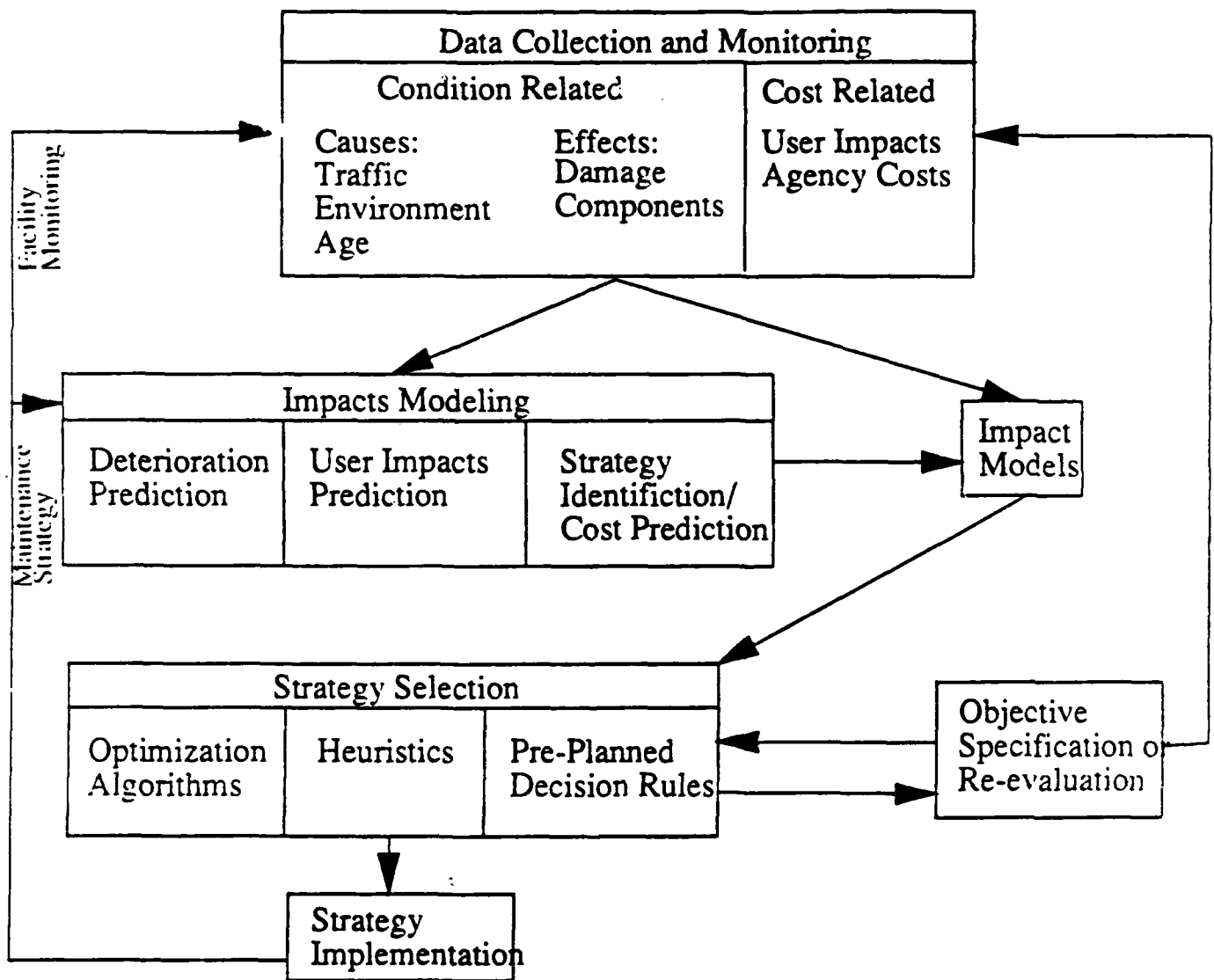


Figure 1.1
The Infrastructure Management Process

thereby affect the five other components of the process. These five components are data collection and monitoring, impacts modeling, application of impact models, strategy selection and strategy implementation. Each component is now briefly described.

Data collection and facility monitoring provide input to the impact modeling phase and to the application of impact models for evaluation and prediction. Two types of data are obtained. The first type is related to the facility and includes causal data or exogenous variables that affect condition. Causal variables include traffic, environment and age that contribute to facility deterioration. Data on facility condition are also used for facility monitoring. These data may be collected using automated methods, subjective judgement or special purpose testing machines or vehicles. The data collection and monitoring may be modified to reflect changes in the objectives. The second type of data are cost related and include both costs to the agency of performing maintenance and costs to the user arising from the condition of the facility.

The impacts modeling component develops three types of models for the evaluation of the impact of maintenance deterioration on (i) current and future facility performance, (ii) users of the facility, and (iii) the agency. The models are

- facility deterioration models for evaluation of facility performance;
- user impacts models that include the effects of causal variables, maintenance strategies and facility performance on vehicle operating costs, ride comfort, safety factors and any other factors that may be related to facility performance;
- strategy identification and cost prediction models that account for agency resource constraints, recognize new technology, and estimate costs either using engineering cost estimates, or statistical methods.

The impact models may be reformulated and estimated or updated as additional data becomes available.

The impact modeling component may be bypassed once satisfactory models are available. The impact models are then used to predict the future pavement performance, possible strategies and current and future impacts and costs. The output from the impact model component is an input to the strategy selection component. There are several possible approaches to strategy selection that may be used independently or in combination. These include

- optimization algorithms such as dynamic programming [5], [6] and optimal control [3] [7];
- heuristics that may be used in knowledge based expert systems [8], [9];
- pre-planned decision rules, such as policies that may be used within simulation [10], [11] or decision analysis [12].

The strategies selected may vary with the objectives selected for the management process as reflected by the interaction indicated in Figure 1.1. The results of this stage give an "optimal" strategy as defined by the objective. This optimal strategy is then implemented.

The strategy implementation component provides feedback to the process as it updates the database to provide information for facility monitoring, additional data for model development, and experience that can be used for model evaluation.

The role of uncertainty in this process has not been fully explored. For example, although uncertainty inherent in deterioration has been modeled the implications of this uncertainty for management decisions has only been recognized through expected values. At the same time errors in the collection of condition data have not been included in the estimation of deterioration curves. The importance of including probabilistic elements in the infrastructure management process is described in Section 2.

This paper develops a framework that recognizes and models uncertainty in all the stages of the infrastructure management process. Special emphasis is given to the integration of errors in data collection with errors in deterioration prediction, since no examples of such an approach

are found in the literature. In Section 2, the motivation for a probabilistic impact model that includes the effects of uncertainties in data collection is discussed. Some concepts relating to deterministic impact modeling, which will be used in later sections, are also described. Section 3 describes the sources of uncertainty in data collection and on the modeling of impacts. In Section 4, the different approaches available in the infrastructure literature and in other fields for probabilistic modeling are described. Section 4 also presents the framework developed in this paper. Section 5 briefly describes the final stage of the infrastructure maintenance management process strategy selection. The nature of the uncertainty and probabilistic frameworks found in the literature are discussed. Section 6 contains a numerical example. The final section identifies directions for future research including identification of data collection needs and areas for model development.

2 CONCEPTS IN MODELING IMPACTS FOR INFRASTRUCTURE FACILITIES

This section develops the impact modeling component of the infrastructure management process and presents examples from the literature that deal with the concepts relevant to the approach developed in this paper. The motivation for a probabilistic approach to the impact modeling component of the infrastructure management process is also presented.

As can be seen from Figure 1.1, the impact modeling component involves the development of three models: (a) A Deterioration Prediction Model, (b) A User Impacts Prediction Model, and (c) A Maintenance Activity Cost Prediction Model. Many models of each of the above types have been formulated in the literature; most of them are deterministic and do not include the uncertainties inherent in the infrastructure management process.

A deterministic impact model calculates only the expected value of the relevant impact. However, in many cases, the expected value is not enough to obtain needs estimates, assess priorities, or select future projects. In addition, calculations with an expected value might

sometimes lead to erroneous results. For a simple example of how two different types of averaging might lead to different results, consider the well known equation for the calculation of PSI [13], the Present Serviceability Index of a pavement. The expression for PSI involves a non-linear slope variance term. Suppose we have n observations of slope variance on a pavement, and we are asked to find the "average" value of PSI for the pavement. The value of the average obtained by calculating the PSI for each individual slope variance measurement and averaging all these PSI values is different from that obtained by calculating a PSI from an average value of slope variance computed from the n measurements. This simple example demonstrates that expected values alone, may give incorrect predictions of facility condition.

A probabilistic impact model provides a distribution rather than a single value for the impact and is therefore a much better representation of reality. Since the approach presented in this paper seeks to explicitly identify the interactions between the different errors present in the data collection and modeling processes, a probabilistic approach is therefore suitable.

A study of the deterministic models in the literature is useful because the formulation presented in this paper uses the same concepts as these models. Some of these models are described in the following paragraphs.

A deterioration prediction model relates some measure of the performance of the infrastructure facility over time to a vector of causal factors that affect deterioration. In the case of highway pavements, the performance measure is usually the PCI or the PSI and the causal factors are some combination of the age, the traffic, climatic conditions, inherent strength and maintenance. An example of such a model is found in [14] relating the PCI over time to the age, traffic and structural number of the pavement. In general, such a model can be written as.

$$S(t) = f(x(t)) \tag{1}$$

where

$S(t)$ is the facility condition of time t

$x(t)$ is a vector of causal variables affecting deterioration.

We call equation (1) the causal equation of performance.

Some models in the literature do not use an aggregate description of performance to model deterioration. Instead, they link individual distresses (such as cracking, rutting, potholes, etc. for pavements) to the vector of causal factors. In such cases, a separate model is estimated for each damage component. Such models have been developed by [15] and by the World Bank [16].

These models can be written for m damage components as follows:

$$M_i(t) = g_i(x(t)) \quad i = 1, \dots, m \quad (2)$$

where $M_i(t)$ is the damage component i at time t . We call the vector

$$M(t) = [M_i(t), i = 1, \dots, m]$$

the damage vector and the set of equations (2) the damage equations.

User impact models and maintenance cost models measure how the facility performance affects the user (in terms of vehicle operating costs, extra fuel costs, tire wear and, if quantifiable, user comfort and safety) and the agency responsible for maintenance and rehabilitation on the facility. User cost models are difficult to quantify and so are not commonly found in the literature. The World Bank [16] uses models of vehicle operating cost based on regression analysis of data from Brazil, the Caribbean, Kenya and India in the Highway Design and Maintenance model. Examples of maintenance cost models are found in [14] who develops models expressing maintenance and rehabilitation cost as a function of pavement condition and M&R activities, and in [17] where the maintenance cost is expressed in terms of traffic loading and climatic conditions on the pavement. Most commonly, cost models are based on unit costs such as the rail performance model [18] and EAROMAR 2 [10]. In general, user impact models and M&R cost models can be written in the following fashion:

For user impact i at time t

$$UC_i(t) = UC_i(S(t), x(t), z), \quad i \in U \quad (3)$$

For routine maintenance cost of activity i at time t

$$MC_i(t) = MC_i(M(t), x(t), z), \quad i \in A \quad (4)$$

For rehabilitation cost of activity i at time t

$$RC_i(t) = RC_i(S(t), x(t), z), \quad i \in R \quad (5)$$

Where UC , MC and RC stand for user impact, routine maintenance costs and rehabilitation costs respectively,

S , M , x are the facility condition, damage and causal variables respectively, as previously defined.

Z is the extent of the facility.

A is the set of all maintenance activities, including varying levels of effort. For example an activity requiring filling 50% of potholes is different from an activity that requires filling all potholes.

U is the set of all user impacts

R is the set of all rehabilitation activities

The above equations can be written in the following general fashion

$$C_i(t) = C_i(S(t), M(t), x(t), Z), \quad i \in (A \cup U \cup R) \quad (6)$$

Equations (3), (4) and (5) state that user impacts and rehabilitation costs of an activity vary as functions of the exogenous causal variables and the overall performance. In practice, for example, trigger values of performance measurements such as PCI or PSI are used to schedule rehabilitation decisions. The cost is therefore a function of the conditions. In the case of maintenance, activities are scheduled as a response to progression of individual damage modes. The cost is therefore a function of the damage vector M .

In this section, some general relationships among the variables of interest in the modeling of impacts were also derived. The whole framework has been deterministic, and uncertainty has not been introduced into the process. In the following section, sources of error that make this framework stochastic are described.

3 SOURCES OF ERROR AND RANDOMNESS

The development of deterioration and cost models involves the specification and estimation of models from data on damage, causal variables and costs collected in the field. Since the data collection process is imperfect, errors are present at this stage. Furthermore, the nature of the functions governing the various relationships discussed in Section 2 are unknown. This causes additional errors in the model specification stage. Finally, even if it were possible to collect data and specify our models perfectly, there is still an inherent randomness in the physical nature of the deterioration process that introduces uncertainty into our formulation. These errors are summarized in Table 3.1.

3.1 SOURCES OF ERROR IN DATA COLLECTION

No data collection procedure is totally precise and error free. In the case of infrastructure, the procedure is further complicated by the fact that it is very difficult to measure some of the causal variables. Variables such as traffic flow are relatively easy to measure, but a variable such as "Quality of Materials," which may affect deterioration, cannot be so easily quantified.

Table 3.1:
Sources of Error in Modeling Deterioration
of Highway Pavements

(A) Sources of Error in Data Collection

1. Inability to measure certain exogenous variables
2. Inability to observe true pavement performance
3. Errors in measuring devices

(B) Sources of Error in Model Specification

1. Inability to include all exogenous variables in the model
2. Incorrect model specification due to insufficient knowledge about the effects of the exogenous variables on pavement condition

(C) Sources of Uncertainty due to Randomness in Nature

At best some imprecise proxy or instrument for the variable can be measured. Another problematic issue is the treatment of maintenance in deterioration models. The effect that maintenance has in forestalling deterioration depends upon three factors:

- (1) the activities that are performed on the pavement
- (2) the level of effort at which these activities are performed
- (3) the effectiveness of these activities, which depends upon the extent as well.

Each of the above factors has its own problems in representation. From the point of view of maintenance planning, it is necessary to include the different maintenance activities as decision variables, but this is infeasible because the large number of activities involved makes the model very cumbersome. Also, different activities involve different definitions of level of effort; for example, the level of crack filling is measured in terms of percentage of cracks filled, while potholes are measured by the number of potholes filled. These noncommensurate quantities also make it difficult to compare the total level of maintenance performed across facilities. Finally, maintenance effectiveness, which measures the amount by which deterioration will be reduced by performing one additional unit of maintenance, is very difficult to measure in practice and is dependent on the nature and the condition of the facility. The representation of maintenance in a deterioration model, therefore, is susceptible to substantial uncertainty.

The same problem appears in the measurement of pavement condition, which is the endogenous or dependent variable in the deterioration equation. The condition of the pavement is a measure of its ability to bear the load for which it is designed. There is no "value" of pavement condition that can be measured directly using a measurement device. The only possible measure is some effect of the condition such as indirect cost to the user in terms of fuel consumption or tire wear (roughness, ride), or the damage incurred by the pavement measured in terms of area of pavement distressed (area cracked and/or the number of potholes). Estimates of pavement condition have to be made from these imperfect damage measurements. This

introduces another source of error linked to the data collection procedure.

Finally, there is the problem of errors in the measuring devices themselves. Even if every exogenous variable and the pavement condition could be measured with a measuring device, the measurements are still subject to the imperfections of the device. In infrastructure, the measuring is often performed by visual inspection which has a very large margin of error. Specifically, the errors in measurement arise in the following stages of the data collection process:

1. Data Acquisition

The errors generated at this stage of the data collection process are due to technological limitations (e.g. camera angle in optical systems), or environmental limitations (e.g. rain causing distortion of an image). Technological limitations include resolution and the speed at which data is collected. For example, for an optical system, the camera shutter speed in imaging frames per second can cause blurring effects on an image if not properly synchronized with the speed of the vehicle carrying the cameras.

2. Data Storing and Recording

After distress data are acquired, they are stored on standard forms, played back on a VCR, or displayed on a monitor, depending on the data collection method used. The portion of data collected to be stored and processed further is subjectively based on perceptions of the extent of distress. For example, if the data collected displays heavy distress observations at a particular location, more of the acquired data would be recorded and stored prior to processing. The remaining data is discarded. The error generated at this stage is a sampling error from subjective inputs.

3. Data Pre-Processing

Data collected is pre-processed into a form more amenable for future analysis. For example, for automated processing, the data is first digitized. The digitized data is pre-processed to remove noise, enhance contrast or to determine the nature of subsequent processing. The pre-processing algorithms depend on the nature of the imaged surface, and the specification of the imaging system. Some surface types (e.g. concrete surface) will require less pre-processing to remove texture effects, noise, etc. The error generated at this stage is a pre-processing error. For visual inspection, such an error could be computed as a percentage of total area distressed for a particular distress type.

4. Object Extraction

From the data collected, objects or features of interest are extracted. The algorithms used for this are specific to particular applications. For example, for pavement surface distress, one would like to extract objects such as cracks, patches, potholes, etc. The desired detail of information to be extracted is also dependent on the application. One would require less information if the objective is just to identify whether distress is present. Alternatively, to be able to distinguish between distress types, and quantify distressed areas, one would require much more detailed information. The error generated at this stage is the object extraction error.

5. Object Characterization

Objects are characterized by a set of physical properties or features; for example, area, distress density, orientation, etc. Characterization error occurs as a consequence of incorrect assignment of a distress pattern to a distress. The pattern used is a representation of features of a particular object of interest, (say a crack) which is used to characterize the

objects observed. Errors at this stage can be termed as "imperfect teacher" errors. For visual assessment by human observers, characterizing distresses is done by comparison with standard photographs or expected appearances, this error type is not very significant.

6. Object Classification

Object classification involves interpretation of a scene of individual distress elements, where a scene is defined as a single frame element, in the case of automated sensing, or a sampling unit in the case of visual inspection. Classification of objects is done using a classification function. This function is a discriminant function which operates in N-dimensional feature space (N is the number of properties used to characterize each object). The error generated at this stage is a classification error. In the case of pavement surface distress, such an error could be classifying a series of disconnected co-linear crack object as a single large crack. Alternatively, another possible error could be classifying a series of alligator, longitudinal, and transverse cracks appearing in the same location (say 3 feet square scene) as alligator cracks.

7. Sample Interpretation

Interpretation of a single sample (scene or frame) is a direct result of the object classification stage. Local occurrences of distresses on a single frame can be identified at this stage. It is the decision of the expert interpreting each sample to make a decision on whether the classification was correct. This leads to a sample interpretation error due to subjective input by an expert.

8. Segment Interpretation

The sample interpretations are aggregated sequentially and analyzed. Unexpected occurrences or nonsequential distress appearances are checked for by a pavement engineer. An

average condition evaluation of the sample is then determined. The results of this process are passed to a database for future performance prediction. A segment interpretation error is generated at this stage by the pavement expert's subjective input.

The magnitude of data acquisition errors for automated visual inspections of pavements has been explored through simulation. The results of this research are presented as a separate paper that is included in the Appendix.

3.2 SOURCES OF ERROR IN MODEL SPECIFICATION

In the preceding paragraphs, the possible sources of inaccuracies in the process of data collection were described. In addition to these sources, our lack of information causes uncertainties in the model specification process itself. The first source of uncertainty is the exclusion of exogenous factors that affect deterioration, and hence pavement condition. The vector of causal factors is therefore incomplete, and the effect of the unobserved variables needs to be included in the deterioration model as a stochastic term.

The second source of error in model specification arises from the fact that the relationship between the observed causal factors and pavement condition is unknown. The specification of the deterioration model is an attempt to capture the effects of the exogenous variables as closely as possible. However, the correct functional form of the deterioration equation is unknown. Any model specification such as a linear one is only an approximation to the "true" specification. The errors arising from this approximation are unobserved.

3.3 SOURCES OF UNCERTAINTY DUE TO RANDOMNESS IN NATURE

Finally, even if every factor that affects deterioration was known without error and the effect of these factors on pavement condition was known, the system would still be stochastic

because of the inherent randomness that is present in nature. This source of uncertainty cannot be isolated since this form of uncertainty cannot be differentiated from that present due to unobserved variables and misspecifications in the model.

The result of these errors and uncertainties is that deterministic deterioration models such as those described in the previous sections are not a complete representation of the deterioration process. Therefore a stochastic deterioration model is used with two components:

- (1) a deterministic component that reflects the expected value of pavement condition over time. This component is the part that can be "explained" by the data; and
- (2) a random component that represents the effects of all the errors and the uncertainties described above.

In the following section, different stochastic approaches to modeling errors are described. The examples are taken both from the infrastructure field and from other fields where stochastic systems are modeled.

4 APPROACHES TO MODELING ERRORS

4.1 DATA COLLECTION PROCESS

Condition and cost data are normally used in the infrastructure management process for prediction of deterioration, user impacts, and M&R strategy identification. In the previous sections, the sources of error in data that go into the impacts modeling stage of the infrastructure management process were described. This section concentrates on the errors in the condition data obtained through surface inspection of facilities. A review of current error analyses for surface condition inspection techniques is also done. The techniques reviewed are mostly from other fields within Civil Engineering and other disciplines [19] [20] [21] [22].

There are a number of data collection technologies currently in use for surface distress evaluation of infrastructure facilities. These range from visual observations performed by humans to automated technologies. Each technology introduces different kinds and sizes of error to the data collection process. These errors are developed, accumulated, transmitted, and apparent in different forms.

The data collection process for any technology (human or machine) involves the use of a sensor (e.g. human eye, video camera). These sensors inspect objects on a pavement surface, and store or record them for processing. This process can be structured in an abstract form as follows:

Object → Inspection → Processing → Output → (distress)

The data collection technology introduces some biases to the representation of the object being observed. These biases can be generally classified as measurement, sampling, or processing biases. A measurement bias could result from inadequate instrument performance (resolution, field of view, imaging limitations), or uncontrollable biases (image distortion due to rain or shadows). A sampling bias arises in the decision of which areas of a pavement segment to inspect, and how much of them to observe. Sampling biases also arise during data reduction and processing, when some data are discarded. Processing biases generally result from interpretation and use of a priori information on pavement distresses while processing collected data. Such biases can be in the form of the characteristics of the features used for classification and interpretation of the collected data. For example, in visual inspection, crack connectivity and attributes are used to classify alligator vs. block vs. longitudinal vs. transverse cracking. A subjective opinion on what attribute values are related to particular crack types may lead to a bias in processing crack information. An interpretation of the data collected is done to find an estimate of the actual object observed. Figure 4.1 gives a summary of the general data collection process.

A data collection process can be designed to do one of many possible things:

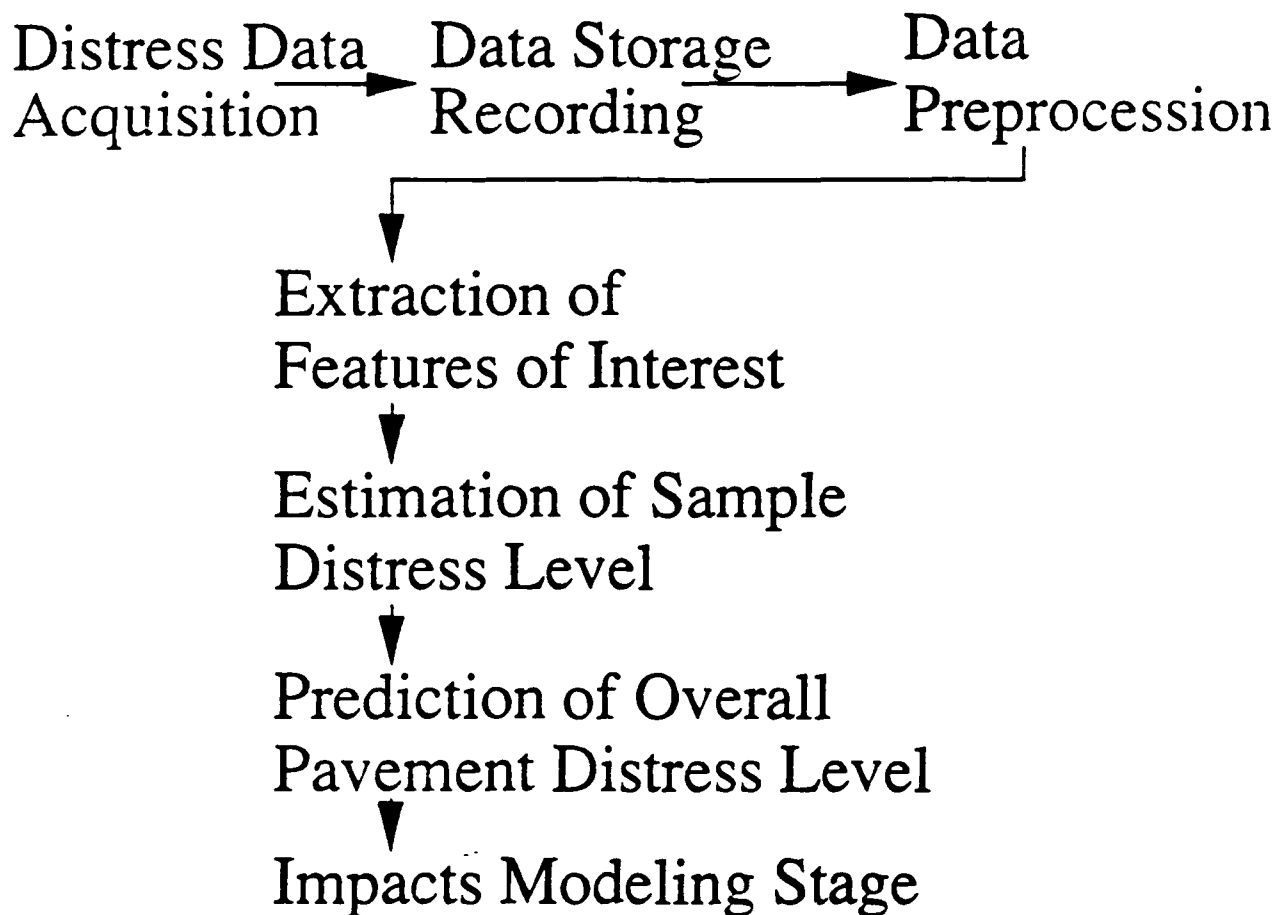


Figure 4.1 Schematic Overview of the Data Collection Process

1. Detect any area or section distressed
2. Recognize the different types of distresses
3. Discriminate or distinguish between distresses
4. Scale the size, extent, severity of a distress
5. All of the above

Following the design of a data collection technology, the identification of distresses from a single inspection or a series of inspections, can be done. The measured distresses are used to compute the condition of a pavement.

A sequence of inspections generates a corresponding sequence of measurement errors. This sequence can be represented as:

$$\hat{d}_{ijk} = d_{ijk} + \epsilon_{ijk}$$

Where:

\hat{d}_{ijk} = measured distress at time i of type j by a technology k

d_{ijk} = value of distress j at time i in the validation data set

ϵ_{ijk} = measurement error of distress type j at time i by a technology k

Taking the possible combinations of \hat{d}_{ijk} into account, will result in a vector ϵ_k of the elements ϵ_{ijk} , which can be used to represent measurement error of technology k. Since the measurements are not made under the same conditions (elements such as weather, deterioration over time, etc.), the distribution of measurement error ϵ_k varies with time as represented by the subscript i. The nature and propagation of this error for specific data collection technologies is analyzed in the following sections.

Models of the different types of measurement errors vary in sophistication with various applications. Past studies have mostly concentrated on a single stage of the data collection

process. For example, Schowengert concentrates on error analysis of the object classification stage in satellite imagery [19]. This work presents three alternative methods of evaluating the accuracy of a classification process. These approaches are:

1. Selecting test area sites from "training" data generated from a supervised classification. Here "training" data is a set of actual images and image features that are used to "train" a classification algorithm into an accurate or desired classification of objects of interest. The classification error is estimated from the deviation of the classified objects from the true objects or actual objects.
2. Using pre-specified test sites generated by an analyst from external information, e.g. ground surveys, aerial photographs, or existing maps, to check the classification accuracy of satellite images.
3. Use of random sampling procedures to generate test sites. The random samples are then divided into two sets of data, one set is used to develop a classifier, the other set is used to estimate the accuracy of the classifier.

In this application map accuracy is defined as the ratio of the number of correctly classified test pixels in a class by the total number of test pixels in the class. The "true" classes of the pixels are determined from independent information, such as ground survey maps and aerial photography. The testing of classification accuracy is done in the form of a contingency table or confusion matrix as shown in Figure 4.2. The assumption made in such an analysis is that, the average accuracy is the sum of the average accuracies for each class, and the overall accuracy is a similar average with the accuracy of each class weighted by the proportion of test samples for that class. While this definition of accuracy recognizes the effect of sampling on classification accuracy, it only holds if the features of any of the various classification classes are independent. This is generally not the case in facility surface features, and even for satellite imagery for crop or vegetation classification as shown in Figure 4.3.

		percent test pixels			# test pixels
		map class			
		1	2	3	
true class	1	84.3	4.9	10.8	102
	2	8.5	80.3	11.2	152
	3	6.1	4.1	89.8	49

$$\text{average accuracy} = (84.3 + 80.3 + 89.8) / 3 = 84.8\%$$

$$\text{overall accuracy} = [84.3(102) + 80.3(152) + 89.8(49)] / 303 = 83.2\%$$

Figure 4.2

Example Contingency Table

Source [19]

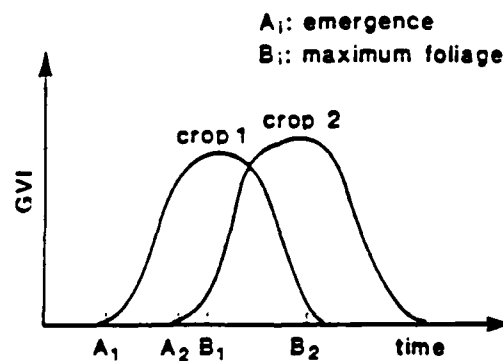


Figure 4.3

Temporal Component of the Greenness Component for Two Different Crops

Source [19]

The reliability of the predicted state of regions outside and between parallel seismic (acoustic) profile lines [20] is another application that models error in measured data. Bayesian techniques are used to evaluate the accuracy of maps produced from a single point or a line of data. "Mapping error" is defined as the percentage of map area misclassified. This is done by comparing the estimated map to the original map. The results of such an analysis were used to evaluate the accuracy of various mapping techniques, and to evaluate the gains of accuracy with increased sampling effort.

This reference presents two methods of estimating mapping error. These are summarized below:

1. Direct method, which uses a finite number of data points. These points are selected from an existing map. A series of concentric circles are drawn about each point. For each circle, the percentage circumference which intersects a given class is determined. A frequency distribution for each radius r of the circles is generated (see Figure 4.4). The accuracy is evaluated as a reliability measure.
2. Indirect method, which is based on statistical estimation using a finite number of observed data points. This method uses the "Nearest-Neighbor Rule", and does not require prior knowledge of the true map. This reference utilized two sampling techniques to evaluate mapping error; mainly, random points and gridded observations. A comparison of the performance of these sampling techniques is given in Table 4.1.

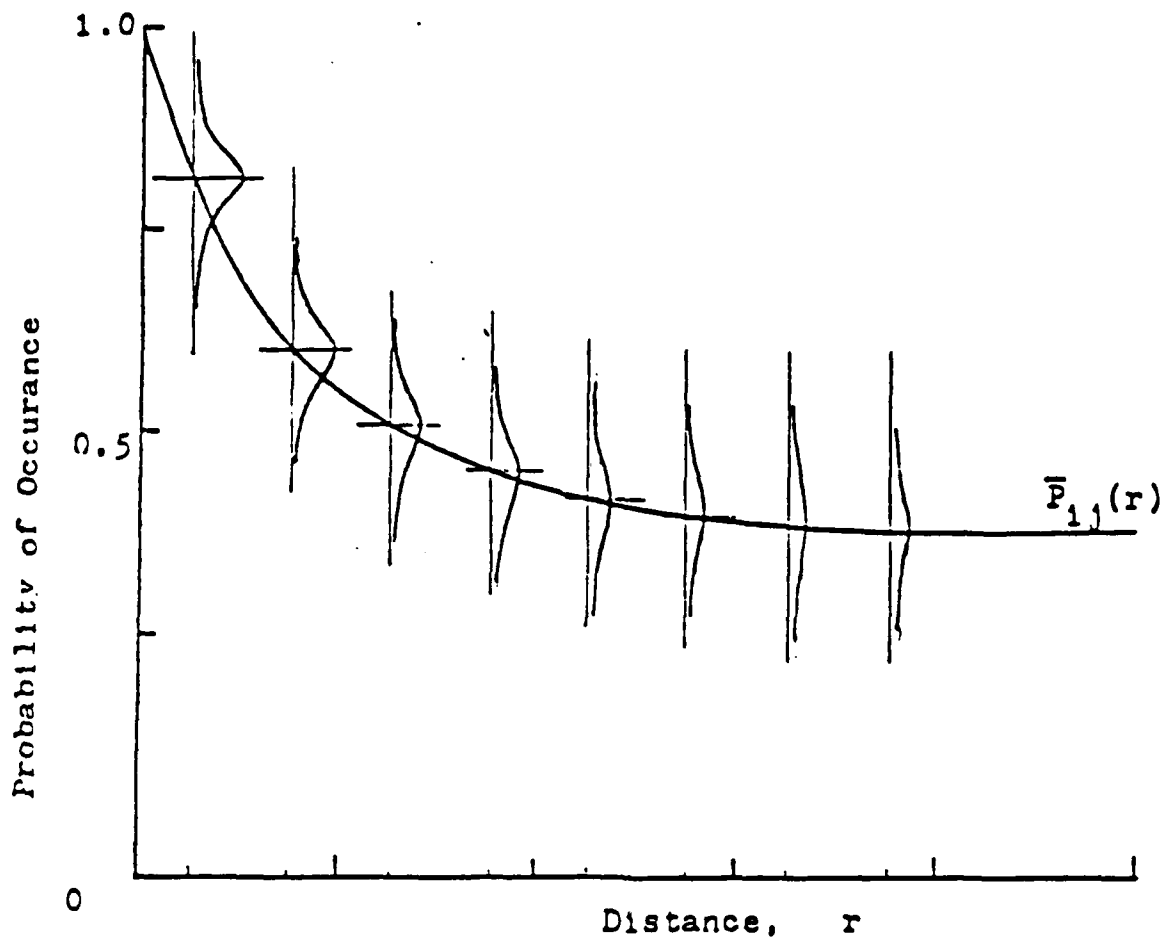


Figure 4.4

Direct Method Probability Decay Function

Estimated Map	Mapping Error	
	100 Random Points	10 x 10 Gridded Observations
Map 1	15.4%	13.6%
Map 2	17.8%	20.0%
Map 3	9.0%	11.1%

Table 4.1
Mapping Error for Various
Sampling Techniques

The smoother the symmetry and the larger the regions on a map, the smaller the mapping error. For example, Map 3 had the smoothest and largest bodies, and portrayed the least mapping error. Map 2 had the smallest and most asymmetric regions, and displayed the largest mapping error. The effect of the size or extent of the area to be classified on classification accuracy is apparent in this analysis.

The applications reviewed above [20] and [19] both looked only at classification errors. These types of errors are yes/no or right/wrong classifications. The correctness of each classification can be represented as a binomial population [19] or a poisson process [20]. For infrastructure surface distress data, the data collection process not only requires the correct classification of objects observed into distress types, but an accurate estimate of the severity and extent of each distress type classified. The error analysis for this kind of data is more complicated. While Schowengert recognizes that there may be errors in the external reference data used to identify the classes in a test site, no analysis of this error was done. Also, the above references, for the most part, required knowledge of the actual or "true" conditions on a map to estimate classification error. Such information is rarely available in infrastructure data collection.

This research recognizes the other errors in the data collection process, and explicitly analyses them. This type of analysis was partially recognized by Brown for concrete bridge deck surveying using photographic methods [21]. This reference evaluated the results of a photographic survey of 8 distress types on bridge decks. A comparison of the defects detected by the photographic method to accurate sketches of actual bridge deck conditions was done as shown in Table 4.2. The results of this research indicated

- the reduction of the data collection apparatus in accurate detection of distresses is important as crack openings less than 0.25 in. cannot be consistently detected.
- distresses with similar features such as crazing, hair cracking, and map cracking cannot be distinguished from each other at crack openings less than 0.25 in.

- longer cracks are more easily detected than shorter cracks of the same width, and that distress types exhibiting a depth dimension (e.g. rutting) that reflect light are more easily noted.
- environmental conditions effect on data collection accuracy.

Type of Defect	Number of Defects Detected		Percent Defects Visible from Prints
	Sketches	Prints	
(1)	(2)	(3)	(4)
Crazing	4	0	0
Disintegration	11	11	100
Hair checking	497	78	16
Map cracking	20	5	25
Pitting and surface scaling	242	142	59
Popouts	44	30	68
Transverse cracks	7	4	57

Table 4.2
Comparison of Defects Detected From Sketches and Prints
Source [21]

A correlation study between subjective evaluation of pavement surfaces vs. instrumental evaluation [22] analyzed correlations between measurements of a scene by a group of evaluators and compared these measurements to the correlations among various instruments. The findings of this study indicate that correlation between different instruments is much higher than correlation between different human observers, particularly when objects inspected have small differences. If a large number of human raters is used, the difference between instrument evaluation and subjective evaluation is reduced. This reference made direct trade-off comparisons between the accuracy, repeatability, and ease of data collection of various technologies.

The literature reviewed recognizes some of the errors in the data collection process. No single reference evaluates all the errors in this process or attempts to quantify interactions and transformation of these errors from stage to stage of the infrastructure management process.

4.2 PROBABILISTIC MODELS OF INFRASTRUCTURE DETERIORATION

In this section, we describe some approaches that have been used to develop a stochastic model of infrastructure deterioration. The first approach that is described was developed for the Arizona Department of Transportation [23] and [24]. In this approach pavement performance is represented by a condition state. The stochastic propagation of deterioration over time is modeled by the probability of transition from condition state i to condition state j in any time period. This probability depends upon the nature of the maintenance performed on the pavement, the load it bears and the climatic conditions to which it is subjected. The effect of different rehabilitation activities is introduced by defining an index to the first crack which is a measure of the amount of time after rehabilitation before cracking begins. This index to the first crack is one of the determinants of pavement condition. The propagation of damage through time is modeled as a Markov process, with future damage dependent only on present condition and condition during the previous year. Roughness and cracking are the two damage types considered, and the deterioration models are used to determine optimal allocation of maintenance resources for a network of pavements over time. A Markov process is also used to model the transition between discrete condition.

Two other stochastic models that have been formulated but not implemented have been suggested for modeling the deterioration of concrete bridge decks. The first [25] attempts to model bridge deck deterioration as a process continuous in state and time. The probabilistic deterioration over time is then modeled as a Wiener process which is a Markov process in continuous state and continuous time. The second approach [26] models bridge deterioration as

a discrete process across state and time, but attempts to introduce the effect of "memory," i.e. make the probability of future state transitions dependent upon past rehabilitation activities and past traffic patterns. Such an approach represents deterioration as a non-Markovian process, unlike the Arizona model. Both these formulations at the present stage of development appear too complicated for any large scale implementation.

4.3 PROBABILISTIC AND STATISTICAL IMPACT MODELING

Probabilistic and statistical impact models have not been widely used in infrastructure management. Statistical cost models, other than least squares fitting of data, have been developed for routine highway maintenance costs and highway construction costs.

The routine maintenance cost models were based on panel data obtained from the Ohio, West Virginia and Pennsylvania turnpikes [27]. The models assume a constant maintenance standard and therefore are not transferable. In developing a highway construction cost model Herbsman [28] reviewed statistical methods based on historical cost records including Box Jenkins modeling and smoothing techniques. Although these methods recognize the inherent variability in construction costs they do not account for economies of scale and technological change. Herbsman developed a statistical model that recognizes that total cost is not the sum of the expected cost of each of the components. The cost model developed by Herbsman includes economic factors and gives expected values and confidence intervals.

Like other cost models, user cost models have generally been developed by least squares curve fitting. However, a stochastic delay cost model has been developed for locks [11]. These models are based on queueing theory recognizing that the arrival rate and service rate for traffic at the lock are random variables with specified mean values. In the most general form the mean arrival rate and service rate are also random variables.

4.4 UNCERTAINTIES IN STRATEGY SELECTION

The role and effects of uncertainty in the strategy selection process have been included using decision analysis [12] [29] [30], simulation [31] [32] [33], and Markov processes [23] [34]. Other approaches used are condition indices reflecting probability of failure, system risk assessment, and a multi-dimensional approach to performance. Each method focuses on a component of uncertainty but fails to address uncertainty in a comprehensive manner. These approaches and their advantages and disadvantages are briefly described below.

Simulation has been widely used in civil engineering to explore the effect of uncertainty on traffic signal operations [35] and other systems that involve probabilistic events [31] [32] [36] [37]. For example, EAROMAR-2 is a disaggregate simulation program for highway pavements. The effects of uncertainty in any of the input variables such as traffic or maintenance effectiveness on the program output may be explored by assuming a distribution for the input variable. Although EAROMAR provides a thorough analysis of deterioration, as with many simulations the program is expensive and time-consuming to run and does not provide solutions.

In a very different approach, decision analysis has been used to incorporate uncertainty in decisions affecting civil facilities in the form of probabilities of the success of a given treatment [38], probabilities associated with different values of roughness and fatigue cracking [Kulkarni 84] and strategies for pavement rehabilitation [40]. Each of these approaches only deals with one source of uncertainty. For example, the probabilities associated with roughness values [39] reflect only the uncertainty in measuring pavement condition.

Alternatively, a Markov decision process with transition probabilities has been used to relate maintenance actions to future road conditions in Arizona [23] (see also Section 4.2). This approach also only includes one source of uncertainty and is constrained to one of two possible problem formulations:

- i) Minimizing discounted average costs subject to minimum standards, or
- ii) Maximizing condition subject to a budget constraint.

A similar approach using probabilistic dynamic programming is being developed for use in the pavement management system, PAVER [34].

The formulations use expected values, and the management strategies are based on the average condition of the network, not the condition of the individual links. Therefore, optimal strategies are expressed as actions for a proportion of links in the network.

Another approach to characterizing uncertainty is the use of condition indices based on probability of failure as a measure of performance. Typically, condition indices are related to a measurable quantity such as cracking, roughness or deflection [41]. Recently, an alternative approach has been used for condition index for sheetpiling associated with a lock [Greimann, 86]. Two condition indices were proposed. The first reflects safety and is defined as the reliability. The second reflects serviceability and is the probability of successful operation (of the lock). These indices reflect more than one source of uncertainty and include information not usually associated with traditional condition indices.

A more complete and unified approach to uncertainty and facility performance was presented by Lemer [43]. Lemer defines performance from the user's perspectives as the manner in which a facility provides the services for which it was intended. He develops three measures of performance:

Serviceability: the degree to which a facility provides satisfactory service to the user.

Reliability: the probability that the facility will provide adequate service over the remaining life.

Maintainability: the extent to which continued effort is required throughout the design

service life.

Although Lemer's work provides a general framework for relating uncertainty, as measured by reliability, to serviceability and the role of maintenance he did not formally formulate or solve an infrastructure investment problem relating performance, including uncertainty, to costs and impacts.

Finally, of particular relevance to civil facilities is work on risk assessment and reliability with respect to systems subject to earthquake damage [44]. These assessment techniques may be particularly useful for quantifying system reliability when transportation infrastructure systems are required to carry abnormally heavy loads for mobilization.

In other disciplines such as manufacturing and the electronic and aerospace industries, well-developed theories of reliability and maintainability (the terms Lemer uses) provide maintenance strategies for different objectives. These theories are not generally applicable to civil facilities due to a number of factors including:

- the prototype nature and large extent of infrastructure facilities. Test panels with replicable experiments for testing components to failure are not practical data sources for constructed facilities that are often large and designed specifically for a particular application or location.
- the variability in environmental conditions. Variability and extremes of physical environment, loads and operating conditions mean that constructed facilities are often subjected to stresses far greater than their intended design.
- the different types and modes of failure. Electronic components commonly work or do not work where a facility may perform, but not satisfactorily.

- the variability in both space and time. The physical size of the facilities and their long lives add additional complexities to the problem. For example, a crack in a facility now may not affect its current performance, but may at some point in the future.

Although, work in other disciplines is not directly applicable, characterizations of repair and its impact on uncertainty as suggested in [45] and [46] may permit the application of Lemer's approach.

At present, optimization models for civil facilities have been developed for several special cases. Deterministic models [3] [47] and [5] and single objective models do not include uncertainty. Furthermore, the use expected discounted costs as an objective function in optimization does not quantify the uncertainty involved in the optimal strategy [37]. Multi-objective models using several objectives have not been widely used due to problems quantifying the trade-offs between objectives. However, they may include uncertainty as measured by reliability as an objective. The most promising optimization approaches are presented in [23] [34] [24] and use dynamic programming. These approaches recognize uncertainty in predicting pavement condition but, as discussed earlier, use objective functions based on expected values.

5 A FRAMEWORK FOR MODELING UNCERTAINTY

The previous section reviewed approaches to modeling uncertainty in components of the infrastructure management process. As discussed in Section 1 the process is sequential with complex interactions that are not captured in the models of specific components. This section reviews the literature in other disciplines where comprehensive approaches have been developed to modeling uncertainty in a decision process. These frameworks may be classified according to their treatment of the uncertainty in both time and space, and the nature of the decisions that are to be made (continuous or discrete). Figure 5.1 shows possible characterizations.

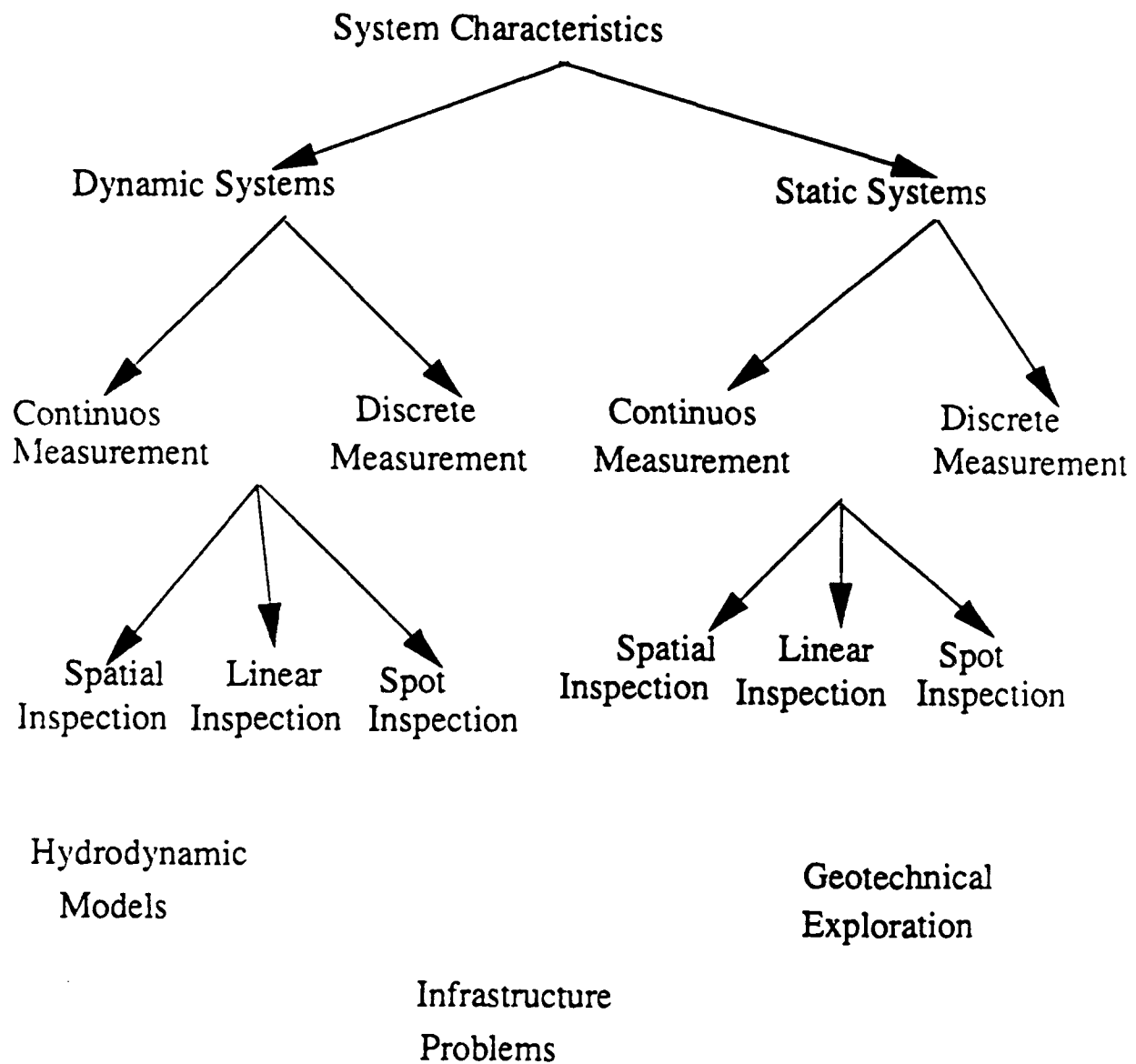


Figure 5.1 Characterization of Data Collection and Modeling

A comprehensive approach to modeling uncertainty in infrastructure management is presented in the remainder of the section. This framework is developed as the approaches used in other disciplines are of limited applicability.

5.1 MODELING FRAMEWORKS IN THE LITERATURE

Modeling frameworks in other disciplines suggest possible approaches to modeling the role of uncertainty in infrastructure management. This section reviews frameworks used for the development of highway improvement programs in site exploration, in transportation investments and water quality modeling.

A number of frameworks have recognized the sequential nature of the management decision making process [12] [29] [30] [48]. However, very few of them allowed for the interaction between these stages of the process. Those that did, such as [30], were developed for a static system, having discrete, spatial inspections (see Figure 5.1). Thus, it is not directly applicable to the infrastructure management process which is a dynamic system, having discrete, spatial or linear inspections.

A decision-theory based framework was developed by Khan and La Fontaine [12] to support the development of highway improvement programs. This framework allows for socioeconomic and political constraints in the definition of highway improvement needs, and selection of beneficial alternatives. Another decision-theoretic framework for urban transportation design and investment decisions was developed by Shallal and Khan [29]. This framework allowed for the direct trade-off between cost of improved data collection techniques and the expected gain in facility cost reduction.

A probabilistic framework for site exploration processes was developed by Baecher [3]. This framework incorporated the sequential nature of the site exploration process into a decision model that allows the optimal allocation of inspection effort.

Mahmassani developed a decision aiding framework for transportation choices under uncertainty [48]. This framework was developed as a decision aid for a class of transportation decision problems in which an analyst is assisting a decision maker in selecting from a large set of finite options whose impact is not known for certain.

In the hydrodynamic field, a number of frameworks have been developed. These include modeling of uncertainty in the forecasting of water quality [31] [32] and input data uncertainty and parameter sensitivity in a lake hydrodynamic model [33].

There is quite a substantial variation in these frameworks and the infrastructure management problem (i.e., conceptual and methodological approaches, system characterization, and decision-making processes). These frameworks are compared in the following sections as to how they differ conceptually to the framework required for infrastructure management

1. Decision-support framework for Highway Infrastructure improvement decisions [12].

The objective of this framework was to advance the management of the highway M&R process by suggesting innovative concepts and methods for the efficient management of this process. These innovations were aimed at the operation, administration, fiscal, and program management stages of the decision process.

This framework allowed for inclusion of uncertainty in predictions of highway infrastructure deterioration causes, specifically traffic, climate, and environmental effects. It, however, did not allow for the explicit inclusion of uncertainty in the deterioration process itself.

The basis for decision-making used in this framework is the physical condition of infrastructure, and the benefits and costs of various alternatives. In the maximization of net benefits, the data collection stage along with its uncertainties and cost implications was not well treated.

The decision-making framework is presented in Figure 5.2. This framework allowed for the inclusion of socioeconomic and political factors in the problem definition stage. However, the breadth of this approach limited the ability to analyze uncertainty in the information acquisition strategies, and link them to the various possible performance levels. Thus, a crucial link between the components of the infrastructure decision process (mainly data collection, deterioration modeling, and alternative selection) is missing.

2. Decision-theoretic framework for urban transportation design and investment decisions [29]

This framework is a narrower version of the broad framework developed by Khan and La Fontaine [12] described above. The basic trade-off developed in this framework is the cost of improved information is expected gain in facility cost reductions. The basic elements of the decision process are:

- Maintenance and rehabilitation actions (a_1, a_2, a_3, \dots), which are the basic choices available to the decision maker
- States of pavement condition (s_1, s_2, s_3, \dots), which are considered uncertain
- Information acquisition approaches (e_0, e_1, e_2, \dots) which imply different levels of investment in techniques and data acquisition for the development of condition estimates
- Possible outcomes (v_1, v_2, v_3, \dots) for any technique or inspection system used
- Costs of data acquisition $C_e(e, v)$ and of condition improvement $C_a(a, s)$.

The decision problem is the selection of the information acquisition approach that results in the best M&R actions for a facility under consideration, and that results in the least total expected cost.

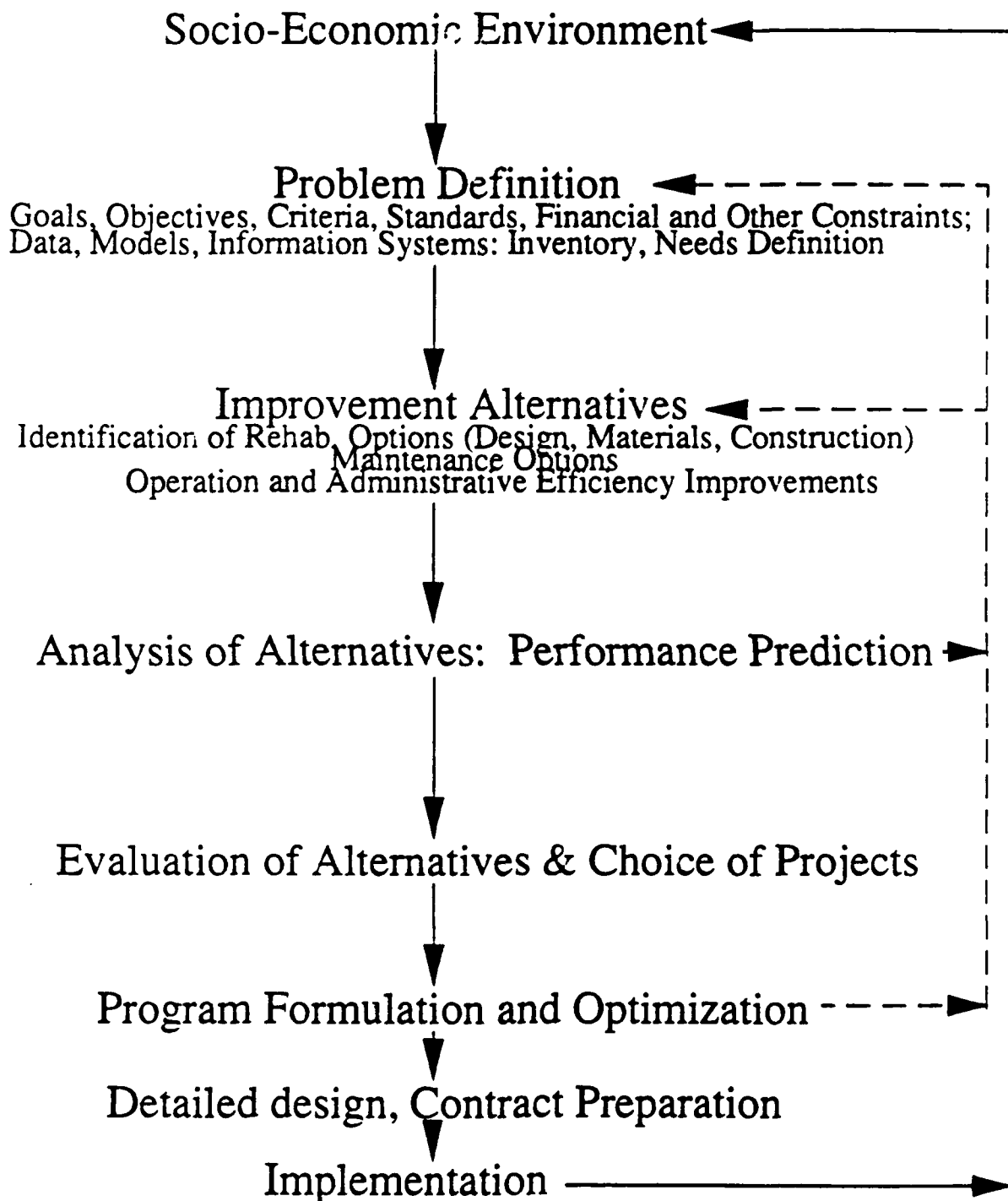


Figure 5.2 The Framework for Decision Making

The decision-theoretic framework is presented in Figure 5.3. This framework recognizes the importance of the data acquisition stage and its relation to the optimal allocation of M&R actions. It, however, lacks a time element in the decision process, and models a dynamic environment in a static manner. An important advantage of this framework is the recognition of the interaction between the data acquisition, pavement condition, and M&R cost modeling stages. It can be summarized as a framework that considers optimum M&R packages, best data collection technology, and total cost minimization.

3. Probabilistic framework for site exploration processes [30]

This framework uses probability theory as an aid in optimizing strategy decisions and in drawing inferences from observed data. It specifically deals with optimizing of inspection effort allocation (i.e. which sites to sample from a given area). It also utilizes probabilistic concepts in pattern recognition for the evaluation of geotechnical patterns.

The exploration process is represented in a model with main components as shown in Figure 5.4. This framework handles two main questions:

- How much effort should be expended in inspecting a network, and how it should be allocated to return the most information
- What inferences should be drawn from inspection data and what are the uncertainties in those inferences.

This framework treats geotechnical exploration decisions and inferences which are "one time" static events that depend heavily on judgement. This approach is applicable to decisions where little knowledge about the behavior or characteristics of a facility is known. It has the disadvantage of not being able to deal with dynamic decision-making systems.

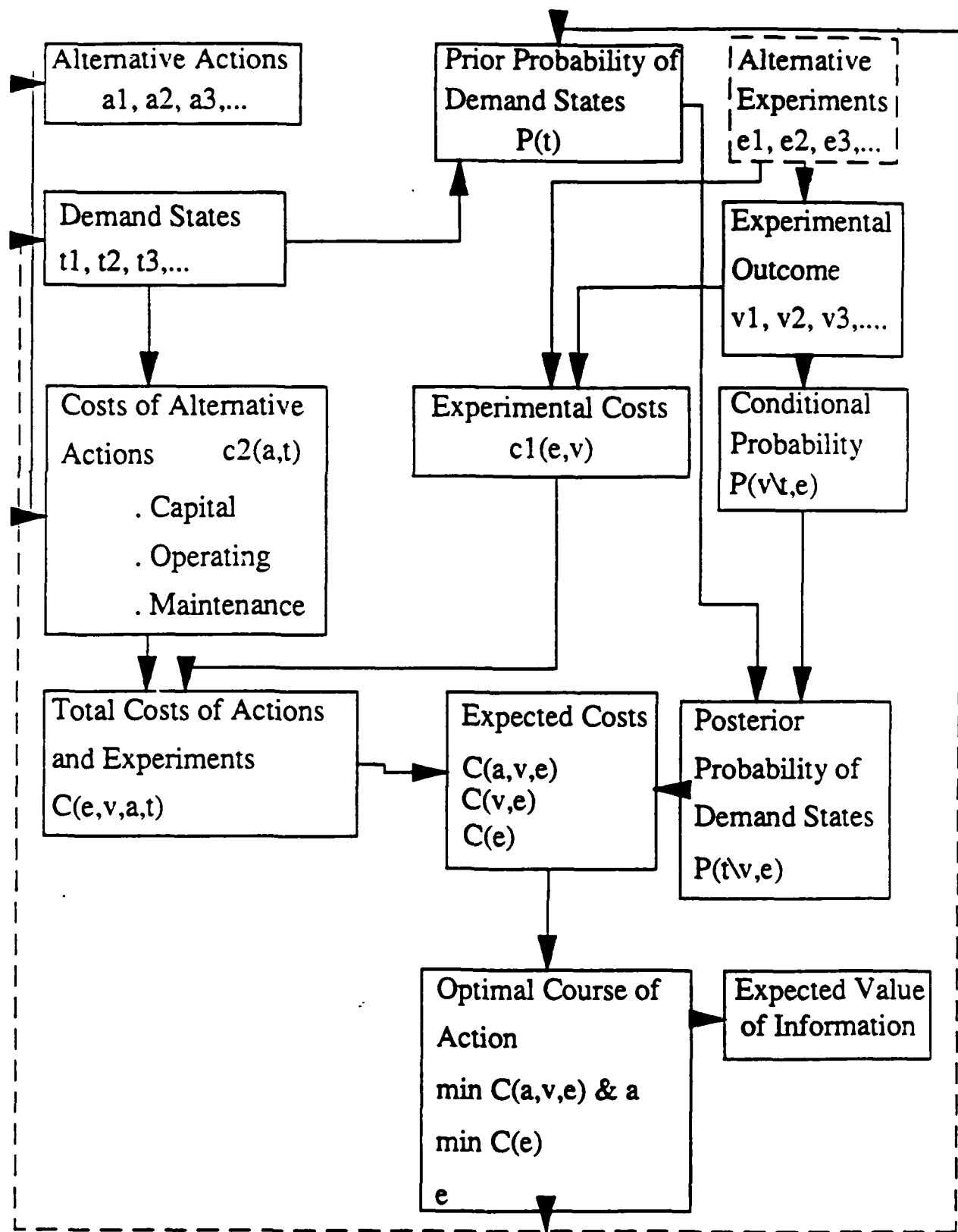


Figure 5.3 Decision-Theoretic Framework

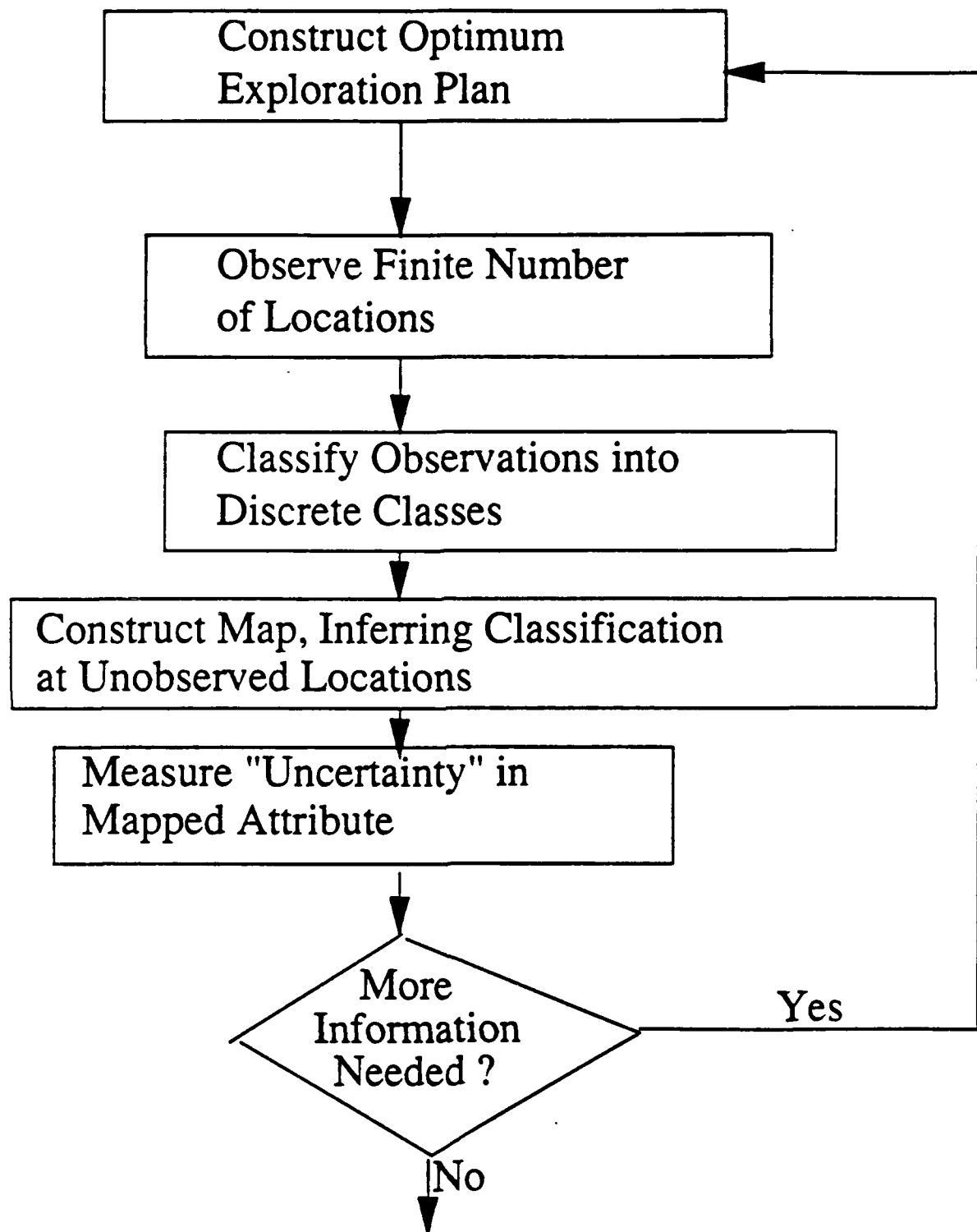


Figure 5.4 Discrete Mapping Flow Chart

4. Decision aiding framework for transportation choices under uncertainty [48]

This framework was developed for transportation decision problems in which an analyst is assisting a decision-maker in selecting from a large set of options whose impact is to known for certain. It takes into account the characteristics of the transportation environment and the behavioral aspects of individual decision-making.

The framework consists of a family of decision rules embedded within a coherent methodological structure. Uncertainty is represented via alternative scenarios, and option impacts are assessed by a single criterion. This structure allows for the inclusion of ambiguity or impreciseness of the preference or value structure on which decision are based, as well as, differing or conflicting opinions.

This framework is useful for the selection of management strategies where political considerations are included. It could act as a powerful addition to the decision-theoretic framework developed by Khan and La Fontaine [12].

5. Uncertainty and forecasting of water quality [31] [32] [33]

A framework for hydrodynamic forecasting was developed in this reference. It differentiates between uncertainty in modeling (parameter sensitivity) and uncertainty in data collection (input data sensitivity). No joint analysis of modeling and data collection uncertainty was done.

This framework allows for the analysis of the behavior of different kinds of models as regards uncertainty propagation. It also allows for the direct trade-off between input data uncertainty and model parameter sensitivity. Thus, one can identify the critical source of uncertainty (e.g. uncertainty in the structure of the model vs. uncertainty associated with predictions obtained from the model vs. uncertainty in the input data to the model calibration).

This framework recognizes the two main uses of data:

- identification of underlying mechanisms of system behavior by use of in-situ data

- testing of speculative hypotheses from a priori knowledge using in-situ data

The effect of uncertainty in input data and the modeling stage differs depending on the respective use of the data.

The approach used in this framework is to assess both input data uncertainty and parameter sensitivity independently, and then compare and contrast the two for different model structures. This recognizes the fact that the decision "to concentrate on data collection accuracy or model development" is based on the consequences of these uncertainties as observed in the final forecast obtained by the model. Unfortunately, however, the data collection and modeling stage are not independent.

The usefulness of the different frameworks discussed in this section and the gaps that have to be filled are summarized below:

The data collection and allocation of inspection effort part of the process was well represented for geotechnical engineering situations [30]. This study developed a framework that would represent the allocation of exploration effort for geotechnical site exploration. Probability theory was employed to develop a methodological approach to site investigation. Measures of evaluating impacts of effort allocation and strategy selection were developed. A number of mathematical tools to optimize the decision process were investigated. The study also investigated trade-offs between cost of experimentation or data collection vs. relative seriousness of making different types of error. This was treated as the cost of decision analysis vs. savings it might lead to in increasing the efficiency of effort allocations, and consequences of large uncertainties in strategy specification.

Geotechnical exploration decisions and inferences are "one time" static events, that are heavily dependent on subjective judgement. The investigation is a spatial inspection of a static system done in a single (discrete) measurement. This is very different from the dynamic, sequential, and inter-dependent infrastructure management decision process. The framework developed in this reference could, therefore, be of limited use.

The inspection data acquisition and processing of inspection data stages were not well treated in the literature reviewed. The study by Somly O'dy on input data uncertainty was found to have some relevant aspects [32]. This study, however, used the simulation approach which is very expensive and requires considerable a priori information.

The modeling, selection of management strategies, and monitoring of facilities were not considered in most of the literature. These stages constitute the largest gap in methodological treatment.

5.2 A COMPREHENSIVE APPROACH

A comprehensive stochastic framework for modeling the deterioration characteristics of infrastructure facilities can now be presented. Section 4 reviewed probabilistic approaches that have been used in infrastructure and other fields to deal with the different uncertainties identified in Section 3. Each approach mentioned in Section 4 developed a methodology to model uncertainty pertaining to just one of the categories mentioned in Table 3.1. In reality, though, each source of error cannot be treated as independent. For example, referring to Figure 1.1, the prediction of user impacts has as an input a measure of facility condition. Any errors in the estimation of facility performance therefore carries through to the performance prediction stage as well. Similarly, the estimation of a performance prediction model requires observed data on causal variables, and errors in data collection are reflected in the deterioration model. The

proper approach to modeling facility deterioration and its impacts is therefore to formulate a model structure where the effects of all identifiable sources of error and the interactions between them are simultaneously considered. Such an approach is described in this section.

The stochastic analog of the causal equation, (that is, equation (1) of Section 2.) This can be written as:

$$S(t) = f(x(t)) + \epsilon(t) \quad (7)$$

where $\epsilon(t)$ is the random error term that accounts for errors in measurements and the errors in specification. Therefore, $\epsilon(t)$ includes in its specification the fact that all causal variables are not known and that the true causal relationship between facility performance and the vector of exogenous factors is unobserved.

The vector $x(t)$ that affects performance is the vector of true causal attributes. In reality, however, we cannot measure the exogenous factors precisely. We call the vector of observed exogenous variables $y(t)$. The relation between the measured and true values of the vector $x(t)$ can be expressed as the following measurement equation:

$$y(t) = g(x(t)) + v(t) \quad (8)$$

where $v(t)$ is the measurement error.

Equation (8) describes the errors in the measurements of the independent variables of the causal equation (7). Errors in the dependent variable in equation (7) are now examined. In Section 2 we stated that $S(t)$ is some measure of performance of the facility, and also stated that in the case of highway pavements, the performance measure traditionally used has been the PCI or the PSI. However, PCI or PSI does not define performance; they are simply two measures of performance. The performance or condition of a facility cannot be observed. Any measure that is used, such as those mentioned above or more disaggregate measures such as damage, are only indicators of performance. In our approach, therefore, performance is treated as an unobserved variable. Various measures that can be used as indicators of performance are assumed to be

available. These measures could be data on extents of individual damage components such as percent cracking, depth of rutting, or number of potholes collected by mechanical devices or visual inspections, or aggregate visual ratings of facility condition (PCI or PSI, for example) or a mixture of both. The relationship between the observed performance indicators and the unobserved pavement condition can be expressed in a form similar to those of measurement equation (8) as follows:

$$I(t) = h(S(t)) + \gamma(t) \quad (9)$$

where

$$I(t) = \begin{bmatrix} I_1(t) \\ \vdots \\ I_m(t) \end{bmatrix} \text{ is a column vector of } m \text{ measured performance indicators.}$$

If $S(t)$ is substituted from equation (7) into measurement equation (9). We then get

$$I(t) = \phi(x(t)) + \delta(t) \quad (10)$$

where ϕ is some composite function of f and h and δ is a composite error term from ϵ and v .

Further substituting from equation (8) for $X(t)$, we can write:

$$I(t) = \phi'(Y(t)) + \delta'(t) \quad (11)$$

where, as before, ϕ' and δ' are composite functions and error terms respectively.

Comparing these equations with the damage equations (2) of section 2 we see that we have here the stochastic analog to those equations, except that we have expressed the equations in terms of measured quantities, x , rather than in terms of the true unobserved quantities of equation (2). The deterministic form of equation (11) gives the traditional deterioration models that are found in the literature.

The measurement equations link the unobserved performance to observed damage. In addition, the observed damage vector $I(t)$ is also a proxy for the true damage vector $M(t)$ defined in section 2. The following equation relates the true damage to the observed damage

$$I(t) = k(M(t)) + \lambda(t) \quad (12)$$

And finally, we have the stochastic analog to equation (6) in section 2, which we can write as follows:

$$C(t) = C(S(t), M(t), X(t)) + \mu(t) \quad (13)$$

where $C(t)$ is a vector of unobserved user impacts and maintenance and rehabilitation costs and $S(t)$, $M(t)$, and $X(t)$ have been previously defined.

We can also write a measurement equation for cost as:

$$OC(t) = OC(C(t)) + \pi(t) \quad (14)$$

where $OC(t)$ is the measured cost.

The equations presented in this section are tabulated in Table 5.1.

The solution to the problem requires the simultaneous estimation of the parameters of all equations in Table 5.1. Suitable assumptions about the nature of the function and the structure of the correlation between the different error terms have to be made. Such an approach simultaneously takes into account all the errors in the deterioration process and the manner in which these errors interact. The approach presented is the proper stochastic approach to dealing with the problem of modeling deterioration of infrastructure facilities.

Table 5.1
Summary of Equations Modeling the Facility Management Process

$$S(t) = f(y(t)) + \epsilon(t) - \text{causal equation} \quad (A)$$

S unobserved, X unobserved

$$y(t) = g(X(t)) + v(t) \quad \text{Measurement equations for x}$$

$$I(t) = h(S(t)) + \gamma(t) \quad \text{performance, tr... damage} \quad (B)$$

$$I(t) = k(M(t)) + \lambda(t) \quad \text{\& true exogenous variables}$$

S unobserved, X unobserved, M unobserved

I observed, y observed

$$C(t) = C(S(t), M(t), X(t)) + \mu(t) - \text{cost and impacts model} \quad (C)$$

C unobserved, S, M, X unobserved

$$OC(t) = OC(C(t)) + \pi(t) \text{ measurement equation for cost} \quad (D)$$

OC observed, C unobserved

A list of notation is given below.

- S(t) - "true" facility performance at time t, unobserved variables
- I(t) - vector of observed indicator variables for performance, usually damage components
- M(t) - vector of true damage components measured by the vector I(t)
- X(t) - a vector of unobserved exogenous variables affecting deterioration
- y(t) - A vector of measured exogenous variables which are observations of X(t)
- C(t) - vector of unobserved user impacts, maintenance costs and rehabilitation costs, expressed as a function of the unobserved variables S, M, and X
- OC(t) - observed cost measurements at time t
- g, h, k, C, OC - functions
- v, γ, λ, μ and π - errors

6 SUMMARY AND DIRECTIONS FOR FUTURE RESEARCH

This report documents a comprehensive approach to modeling uncertainty in infrastructure management. This includes:

- identification of the elements of the process that are influenced by uncertainty,
- recognition of the sources of error and randomness in the process,
- review of predictive and explanatory models that account for uncertainty in the process,
- development of a comprehensive framework that explicitly includes uncertainty in stochastic exogenous variables and endogenous variables by modeling the variables as random variables with a deterministic and stochastic error component.

The results of the research are for use in decision making using optimization approaches found in the literature that are based on expected values. Before the research can be implemented further research is required to:

- hypothesize and test distributional assumptions for exogenous variables such as weather and inherent variability,
- develop and estimate functional forms for the models developed in this phase of the research.

In the development of the comprehensive framework the research has also identified the need for an estimable, rational indicator of condition and the importance of uncertainty in the selection of technologies for data collection. Future research will concentrate on the development of the comprehensive framework, the use of latent (unobserved) variables as indicators of condition and the representation of the data collection technology in deterioration modeling.

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8 APPENDIX: EVALUATION OF AUTOMATED INSPECTION SYSTEMS FOR PAVEMENT SURFACE DISTRESS

DRAFT

**EVALUATION OF AUTOMATED INSPECTION SYSTEMS
FOR PAVEMENT SURFACE DISTRESS**

Paper Prepared for Presentation at the 14th ARRB Conference
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Abstract

The extent of degradation and decay of transportation infrastructure has created new demands on maintenance management systems. This also creates a need for accurate condition assessment data for use in infrastructure management. At the same time technological advances in automated inspection systems provide the opportunity to automate the collection of surface condition data. The automation process creates large amounts of data, most of which are removed during processing to highlight features of interest. The effect of the technology on accuracy has not been previously evaluated. The errors in data collection, and the relationships between the data requirements for a management system and the selection of the appropriate data collection technology for pavement surface distress are explored in this paper. This includes the evaluation of alternate automated sensing technologies and inspection frequency, identification of the main sources of error and the nature of error propagation, investigation of analytical error quantification tools, and selection of a measure of system accuracy. Simulations are used to illustrate the results.

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1 Introduction

1.1 Background and Motivation

The extent of degradation and decay of transportation infrastructure has created new demands on maintenance management systems. This, in turn, has created a need for accurate and timely condition data for use in infrastructure management. Technological advances in automating the inspection process have made available large amounts of data, most of which are discarded during data processing. The data collected serves a number of purposes, some of which are

- **Research and Development:** Designing automation systems, or studying the relationships between condition measures and possible causal variables
- **Strategy Selection:** Selection of pavement management programs e.g., rehabilitation and maintenance actions, or inspection strategies
- **Monitoring and Evaluation:** Monitoring condition related causes and effects of damage, or evaluating the performance of data collection technologies.

The future use of the data collected using a given technology dictates the system specification and accuracy requirements of this technology. For example, research and development programs may require detailed locations and dimensions of distresses on a pavement, whereas a monitoring and evaluation program may require less detailed, but replicable measures of distresses.

Past research has concentrated on the feasibility of automated technologies for pavement distress evaluation. These studies have concentrated on investigating and comparing hardware and software needs, data collection procedures, merits such as cost and accuracy, and limitations,

or on designing new automated technologies for data collection [1,2]. The impacts of the merits (accuracy) and limitations (resolution, field of view) on the future use of data have not been evaluated.

1.2 Objectives

This paper explores the errors in data collection, and the relationship between the data requirements for a management system and the selection of the appropriate data collection technology for pavement surface distress. This includes identification of the main sources of error and the nature of error propagation, investigation of analytical error quantification tools, selection of a measure of system accuracy, and evaluation of alternate automated technologies at various inspection times and frequencies. Simulations are used to illustrate and investigate the above.

1.3 Problem Definition

Automated technologies have been introduced to replace or complement current data collection techniques. Currently, pavement condition data is collected by a variety of human observations [3]. These are visual inspections of a sample pavement surface. The evaluators record defect types, extents of distress, and severity levels. Distresses appearing in the observed (sampled) sections are used to predict the overall state of the pavement. Visual surveys tend to be considerably subjective, and almost always lead to inconsistencies in distress detail over space and across evaluations. In addition they require extensive time and resources for data collection. Given current constraints in time and resources, visual techniques are limited to small sample sizes, simple record keeping procedures, and infrequent data collection. The advantage of visual inspection techniques, however, is the visual verification of actual conditions.

Several technologies for automated detection of surface distresses have been developed recently. These are generally faster, more objective, and more consistent than human observa-

tions. Since these systems have not been operative for long, and are mostly in the development and testing phase, their accuracy and performance is not known. To test their performance, one needs to know the actual condition of the pavement inspected. These tests can be done with complete confidence if one observes the entire pavement, and checks each distress actually present against one detected by an automated technology.

The pavement surface evaluation problem has some specific aspects which lend complexity to the testing of accuracy and technology performance. These aspects are described below:

1. Missing measurements or data -- At any point in time, the ability to know the actual state of a pavement is limited by the lack of the necessary data. This is due to resource limitations which may lead to inadequate sampling (either spatial or temporal), and significant gaps in the information required to accurately know the pavement condition.
2. Time dependent changes of pavement condition -- As a pavement deteriorates or as corrective or preventive action is performed on a pavement, the measures of surface distress change. It is thus difficult to correlate past measurements with current or future measurements to estimate accuracy levels of data collection systems.
3. Variety of measurements -- Pavement surface distress data is collected by various evaluators and by various methods. These evaluations may range from unstructured verbal comments to detailed reports revealing significant features of a pavement's surface condition. The coordination of these different types of data to evaluate data collection system performance is a major task.

Therefore, there are errors in the validation data as well as in the automated technology's data. For example, if the automated technology is an optical sensor and the validation data set was obtained from a visual inspection, the scenarios include:

- (a) The optical sensor observes a distress (say a series of disconnected co-linear cracks), and classifies it as a single large crack. A visual inspection of the same distress identifies it correctly as a series of co-linear cracks. This identifies an error in the optical sensor's automated process.
- (b) The optical imaging system identifies a correct location of a distress, but the matching of this location with one identified by a visual inspection may not be exact (in space) due to sampling limitations. This leads to a conclusion that the optical system is in error, when it really is accurate.

No attempt has been made in the past to estimate or identify such errors. Most of the error analysis for automated technologies has been carried out assuming the data used for validation is accurate [4,5,6]. This paper traces the errors developed and accumulated by a simulated optical data collection process, and tests the sensitivity of these errors to errors in a validation data set collected by visual inspection. This involves analysis of the error generation process in data from human observations as well.

2 Data Collection Process

2.1 General

The data collection process for any technology (human or machine) involves the use of a sensor (e.g., human eye, video camera). These sensors inspect objects on a pavement surface, and store or record them for processing. This process can be structured in an abstract form as follows:

Object → Inspection → Processing → Output (distress)

The data collection technology introduces some biases into the representation of the object being observed. These biases can be generally classified as measurement, sampling, or processing biases. An interpretation of the data collected is done to find an estimate of the actual object observed. Figure 2.1 gives a summary of the general data collection process.

A data collection process can be designed to do one of many possible things:

1. Detect any area or section distressed
2. Recognize the different types of distresses
3. Discriminate or distinguish between distresses
4. Scale the size, extent, severity of a distress
5. All of the above

Following the design of a data collection technology, the identification of distresses from a single inspection or a series of inspections, can be done. The measured distresses are used in numerically valued functions to compute the condition of a pavement.

A sequence of inspections generates a corresponding sequence of measurement errors. This sequence can be represented as:

$$\hat{d}_{ijk} = d_{ij} + \epsilon_{ijk}$$

where:

\hat{d}_{ijk} = measured distress at time i of type j by a technology k

d_{ij} = value of distress j at time i in the validation data set

ϵ_{ijk} = measurement error of distress type j at time i by a technology k

Taking the possible combinations of \hat{d}_{ijk} into account, results in a vector of errors, $\underline{\epsilon}_k$, which can be used to represent measurement error of technology k . Since the measurements are not made under the same conditions (elements such as weather, deterioration over time, etc.), the

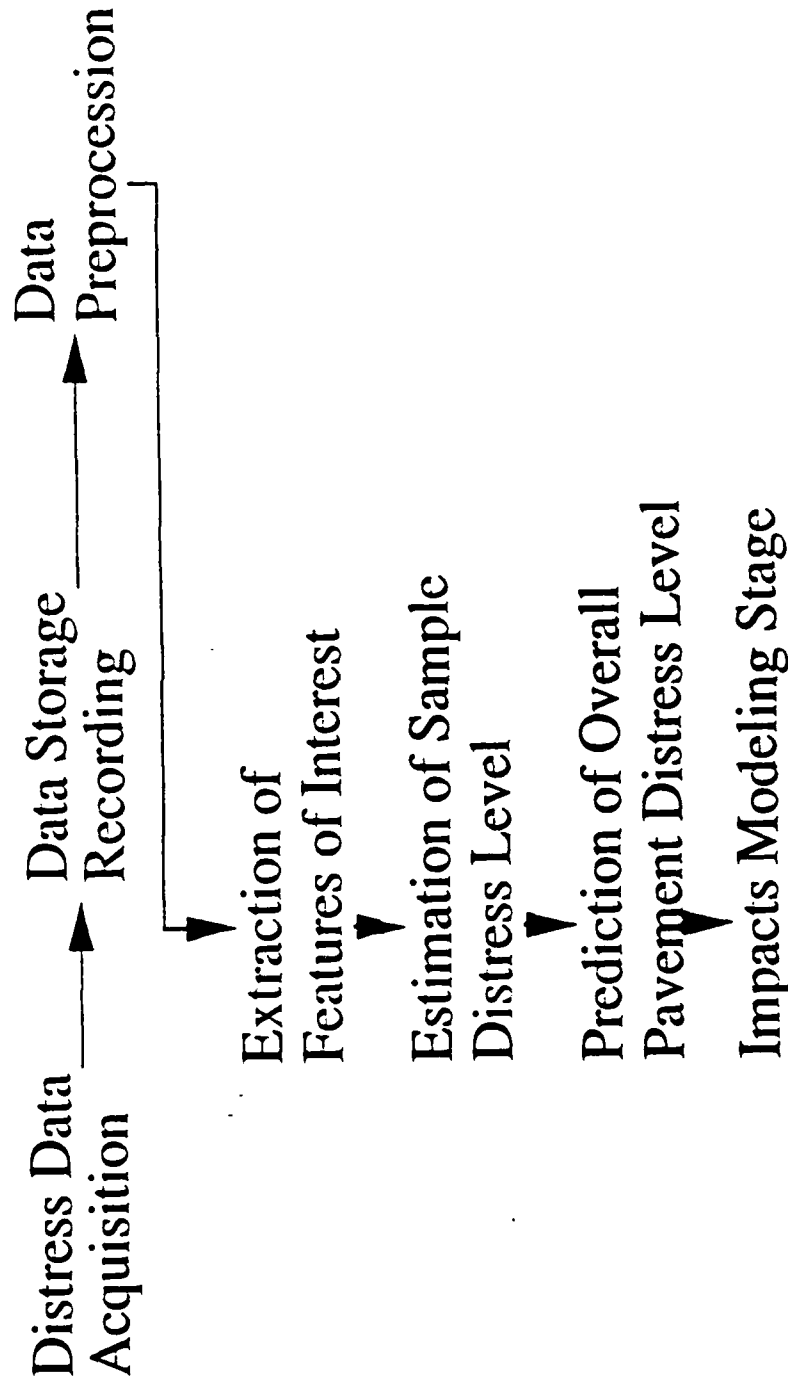


Figure 2.1 Schematic Overview of the Data Collection Process

measurement error ϵ , does not occur with equal probability over time and across locations. The nature and propagation of this error for specific data collection technologies is analyzed in the following sections.

2.2 Data Collection Techniques

2.2.1 Visual Inspection

The types of distress data collected by state agencies are typically roughness (ride), structural (deflection), surface distress, and skid resistance [7]. This paper concentrates on surface distress. Surface distress can be defined as a measure of pavement fracture (cracking), distortion (faulting), and disintegration (raveling). This information is acquired by subjective visual inspections recorded on standard forms.

Typically, sections of 100 to 500 ft. at 1 mile intervals, or areas of 1500 to 2500 sq. ft. at various mile intervals are surveyed [8]. Various disaggregate condition measures such as percentage area distressed, or aggregate measures, such as PCI, PSI are estimated from such inspections. The quality of data is subject to the size of samples and the accuracy of record keeping and measuring procedures.

2.2.2 Automated Technologies

A significant number of past research projects have investigated the possibility of automating the pavement surface condition evaluation process. Several technologies have been developed utilizing a variety of concepts and approaches. This section will concentrate on the investigation of optical techniques for automated pavement crack detection.

A summary of the techniques identified in a literature review is given in Table 2.1. Three such techniques have well documented accuracy and performance information such as resolution, field of view, imaging rate, and some processing procedures. These are detailed below.

TABLE 2.1
AUTOMATED PAVEMENT CRACK DETECTION TECHNOLOGIES
Source: Adapted from [1]

Data Collection System	Manufacturer or Researcher	Merits	Limitations
Short-exposure video (ACM)	KLD Associates	<ul style="list-style-type: none"> • mature technology • inexpensive hardware • reusable recording medium • readily processed 	<ul style="list-style-type: none"> • field of view limitations • requires strobe lights • shuttered system causes imaging limitations
Video (ADDA)	University of Waterloo	<ul style="list-style-type: none"> • as above with no field of view or imaging system limitation 	<ul style="list-style-type: none"> • limited resolution
Continuous line scan	Earth Technology	<ul style="list-style-type: none"> • less light field uniformity required • real time signal processing • medium-high resolution 	<ul style="list-style-type: none"> • complex processing and interface • custom hardware design

1. Automated Crack Monitor System (ACM)

An automated crack monitor (ACM) for measuring cracks in roadway surfaces was developed by KLD Associates Inc. This was done under a contract for Federal Highway Administration. The design was based on video technology. The image acquisition phase of the system was presented in considerable detail [9].

The system utilizes two video cameras providing a resolution of approximately 0.05 in (1.25mm) over a field of view of 3 ft. laterally by 2 ft. longitudinally. A high intensity gas discharge strobe light is used to illuminate the pavement surface. This light source freezes the images while traveling at a speed of up to 40 m.p.h. This limits imaging to six frames per second. At a 40 m.p.h. speed, the sampling rate in one 3 ft. wide frame pair every 20 ft. (10% sampling). The sampling rate can be increased by decreasing the speed of the vehicle. Figures 2.2 and 2.3 show the framing pattern and the sampling relation to speed of travel respectively.

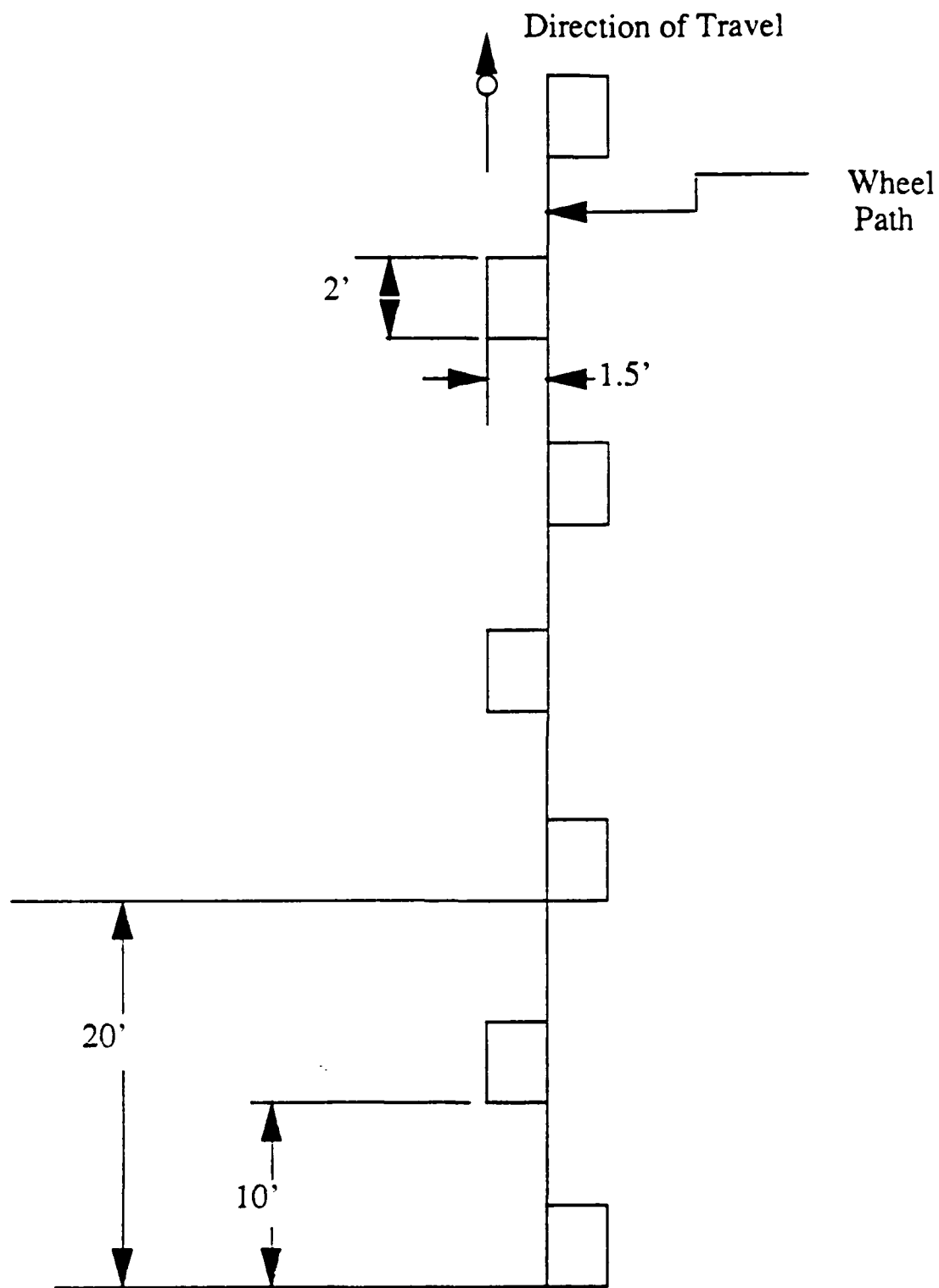


Figure 2.2 Framing Pattern to cover 10% of roadway with a two camera system
[Source 9]

Sampling Rate (Images/second)

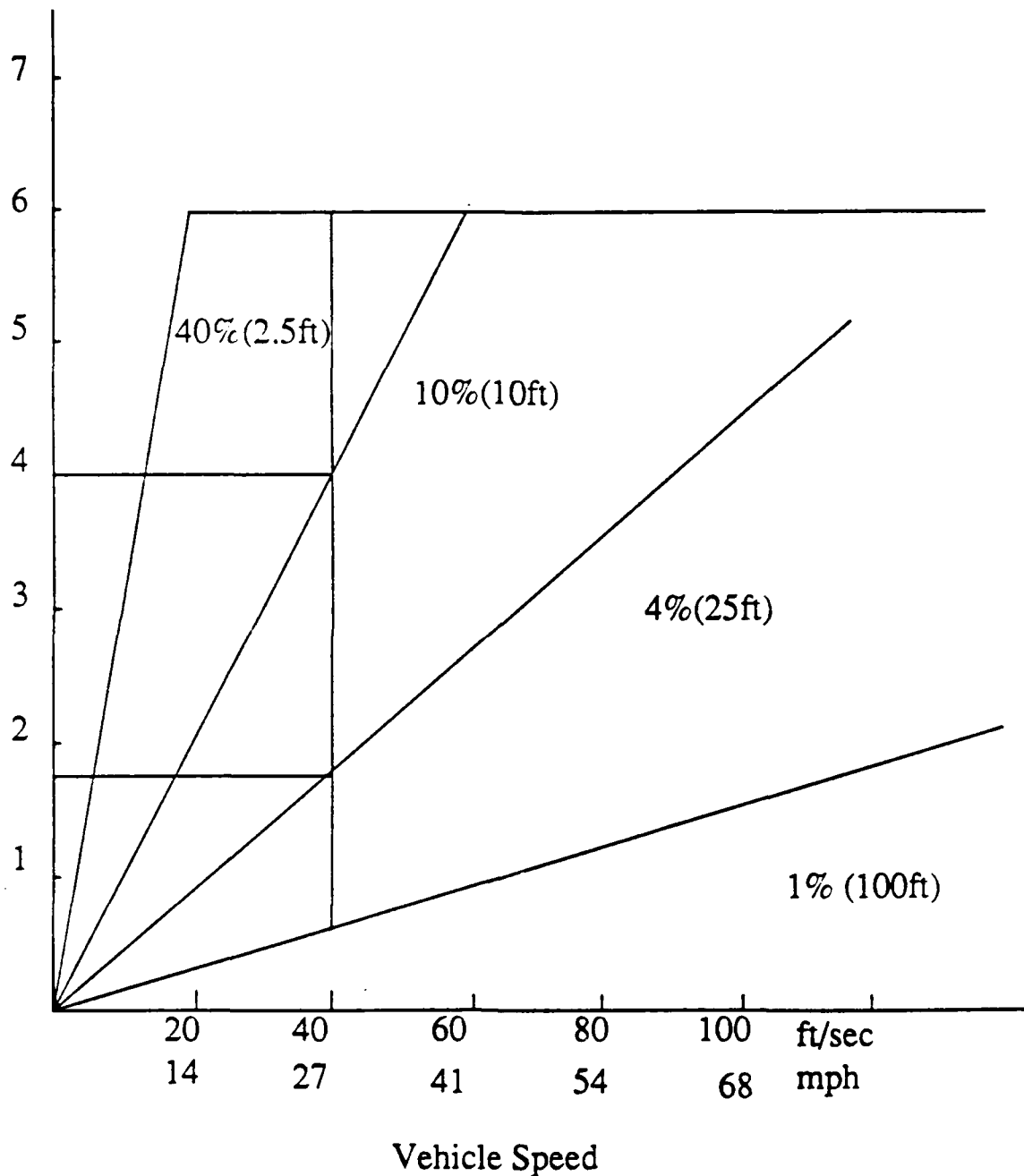


Figure 2.3 Sampling rate vs vehicle speed for various % of roadway covered

[Source 9]

The above discussed system results in a discontinuous staggered image pair, which is quite small. The recognition of distress features is, therefore, more subject to errors of improper recognition or partial recognition of distress.

2. Automated Distress Data Acquisition (ADDA)

ADDA was developed by the University of Waterloo under the sponsorship of the Ontario Ministry of Transportation [10]. The system utilizes a video camera mounted on a vehicle traveling at a maximum speed of 30 km/hr. The width of the field of view of the system at its midpoint is 14 ft. at a camera angle of 35 degrees from the horizontal. Figure 2.4 shows the general specifications of the system.

The resolution of the system is 512 x 512 pixels with 128 possible gray levels each. This translates into a resolution of about 0.34 in. The resolution of the system is reduced during processing by the VCR and TV used. This lowering of resolution introduces errors in the identification and classification stages of the analysis. The resolution is further decreased by the blur in the image due to the forward motion of the vehicle.

The image objects used in the interpretation stage are the vertical and horizontal edge elements. Longitudinal, transverse, and alligator cracks are distinguished using decision boundaries as shown in Figure 2.5. The edge detection algorithm leads to the misclassification of edge producing objects such as patches, potholes, bleeding, and uninteresting blobs as alligator cracks. The edge detection approach and the other limitations of this system are further analyzed in the following sections.

3. Multi-camera Video Sensing using Microprocessors (PCES)

This system is being developed by the Earth Technology Corporation, as part of an overall pavement condition evaluation system [11]. Microprocessor measurement techniques are applied on a multi-camera video system mounted on a van-type vehicle. The system utilizes four, one-dimensional CCD arrays, that can observe a 12 ft. lane of road surface. The

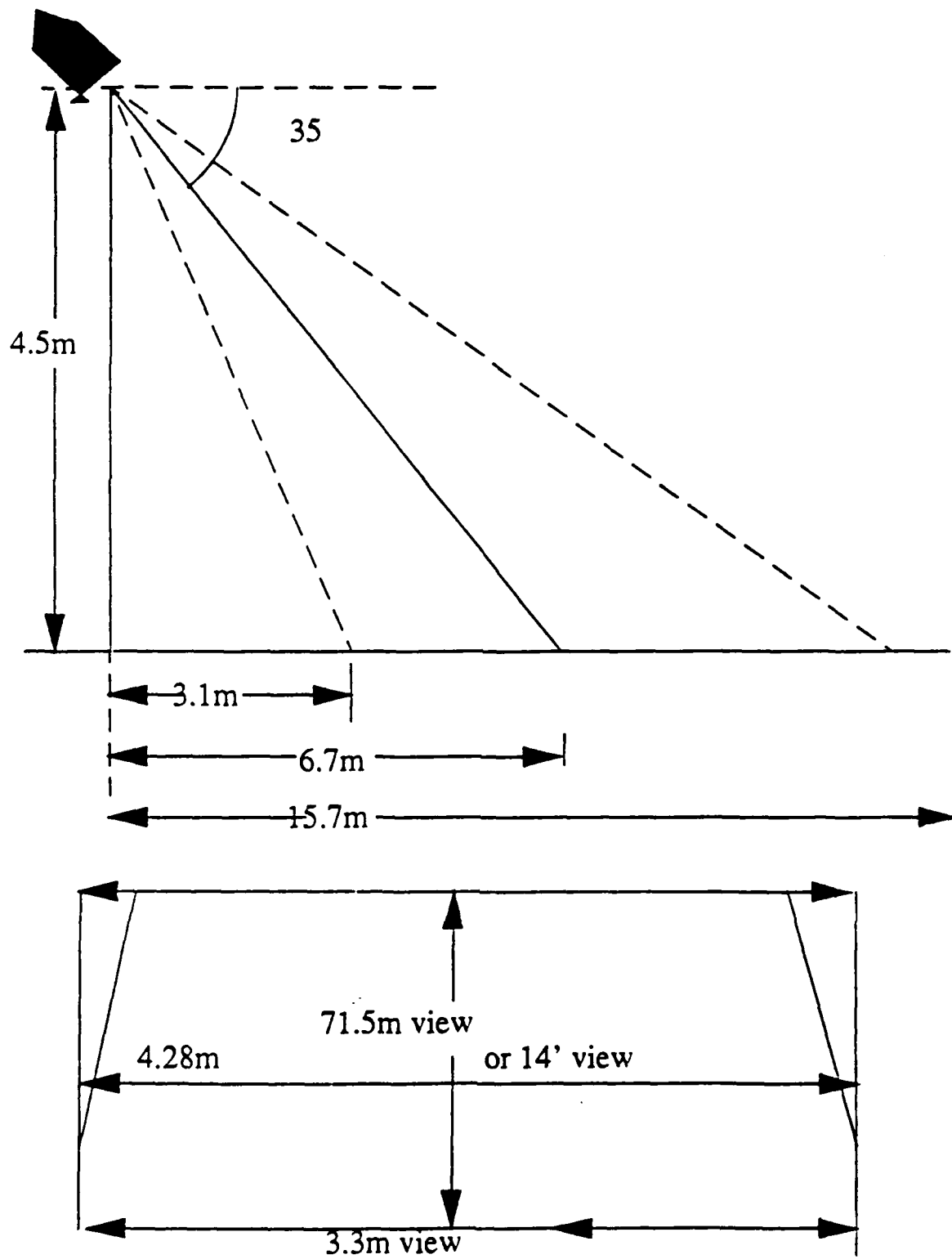


Figure 2.4 Field of Vision
[Source 10]

Number of Vertical Edge Elements (x1000)

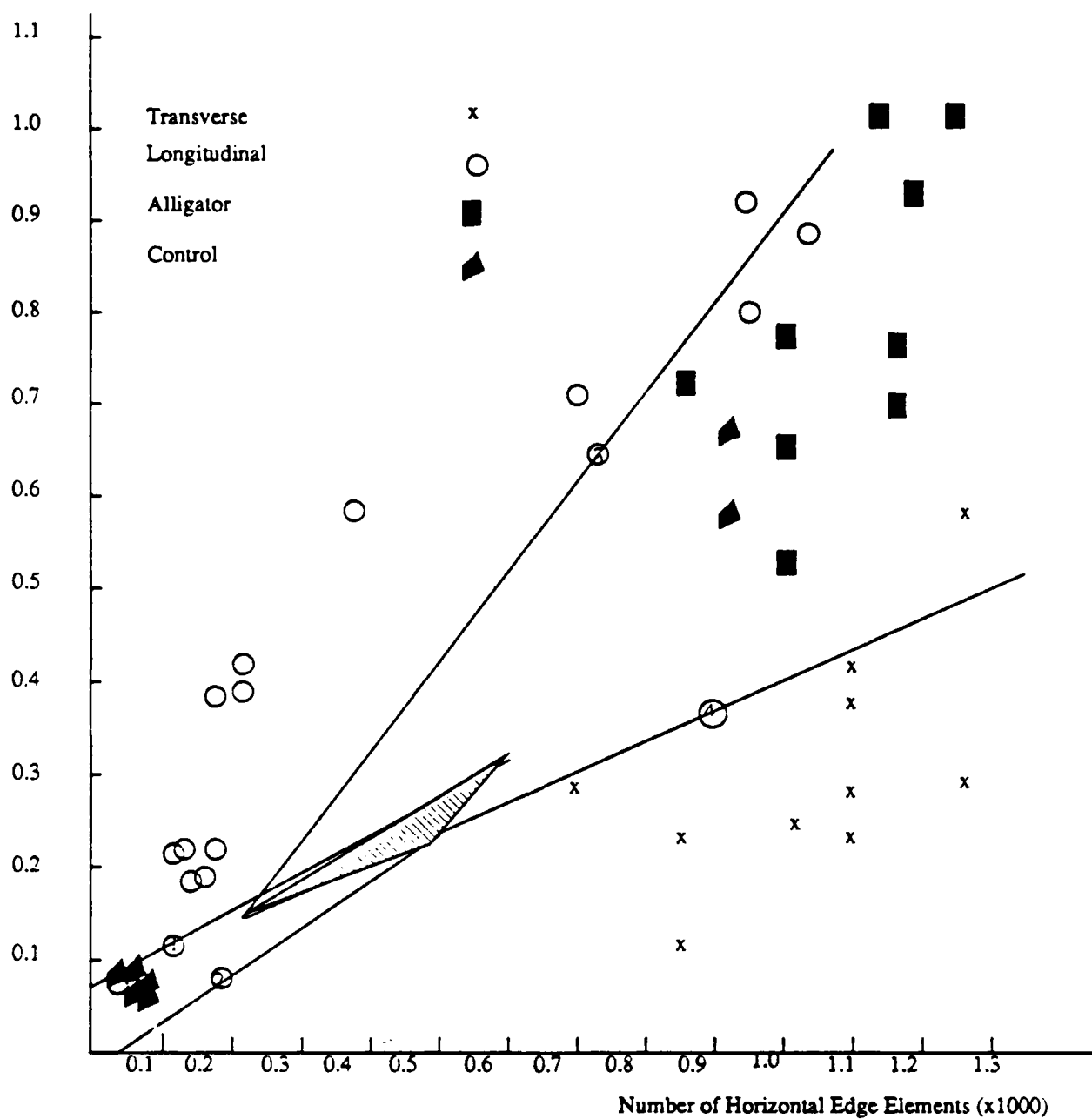


Figure 2.5 Decision Boundaries
[Source 10]

assumption made in this system is that less than 100% of the pavement area is sampled to allow for real time processing. Figure 2.6 shows the details of the linear scan process. The specific algorithms implemented and their respective accuracy has not been reported. The literature reviewed indicates the use of a crack validation algorithm which will detect cracks in relatively new pavements. The algorithm uses crack shape factors to identify cracks. Other attributes used are crack area, crack direction, crack width, length, and depth. Since no information on the resolution of the system was available, this system was not further investigated.

3 Errors in the Data Collection Process

3.1 Performance of Data Collection Systems

The output of any data collection system includes error. These errors can be specified for a particular object being measured (e.g., an individual crack on a scene), for a particular scene (e.g., a single frame or sample element), or as a total expected error over the set of measurements (e.g., interpretation of an entire sample).

The selection of the level of aggregation depends on the impacts of an error. An example of such impacts could be a reliability measure of different error types. Some possible specifications are summarized below:

1. Probability of incorrect identification -- This is defined as the probability of identifying a distress type measured as different from the actual one.
2. Probability of a misprediction -- This is defined as the probability of incorrectly estimating or forecasting distressed areas. This may be due to unobserved detail leading to an erroneous estimate of the extent or severity of a distress. Technological factors affecting such a measure could be resolution or field of view limitations.

55 MPH
10 Mhz Clock
51.2 usec per scan line
26.2 Msec per frame

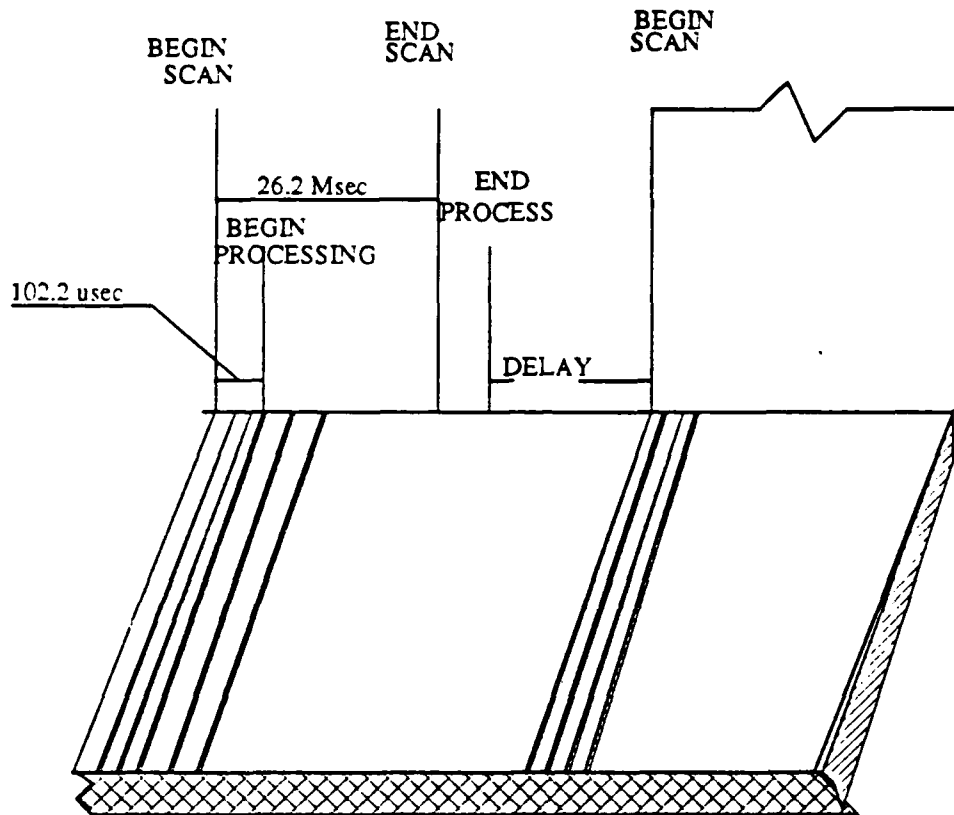


Figure 2.6 Linear Scan Processing
[Source 11]

3. Probability of accurate prediction -- This is defined as the probability of predicting correctly the distressed areas. It is the complement of the probability of a misprediction and can be used as a measure of accuracy of a technology.

The second and third measures of system performance were used in this paper. Analysis was done based on ranges of performance of a technology on a single distress to performance over the life of a pavement. Section 4 gives a more detailed description.

3.2 Effect of Errors on Data Collection

Errors in data collection have varying effects, including:

1. Requirements for larger sample sizes: To be able to accurately estimate or identify distressed areas on pavement sections one requires a very large set of observations. The lower the viewing capability of a technology (resolution, field of view), the larger the sample size required.
2. Requirements for more frequent inspection: Most automated technologies depend on a prior expert knowledge to post-process the data acquired. The nature of the post-processing makes it highly dependent on the average distribution of distress extents and severities. Since this distribution is time dependent, and it is difficult to incorporate time changes during processing, one needs to make more frequent inspections to account for the temporal changes a pavement is undergoing. Thus, processing errors affect the frequency of inspections by a technology.

The above mentioned limitations can be corrected for statistically. However, extensive data is required to statistically estimate the errors, so this solution approach is limiting. These effects can be generalized as

- pre-data collection, such as choice of sampling size and inspection frequency;
- data collection, such as actual area observed by a technology; and

- post-data collection, such as processing errors.

This paper concentrates on the data collection errors.

3.3 Definition of Data Collection Errors

The data collection errors analyzed in this paper can be classified as imaging system errors. Other error types are processing errors, and subjective input errors. An assumption made here, is that these other errors are negligible. This assumption was necessary in order to evaluate existing technologies. The components of this error type and the mathematical notation used are:

$\epsilon_{r,jk}$ = resolution error for distress type j at time i for system k

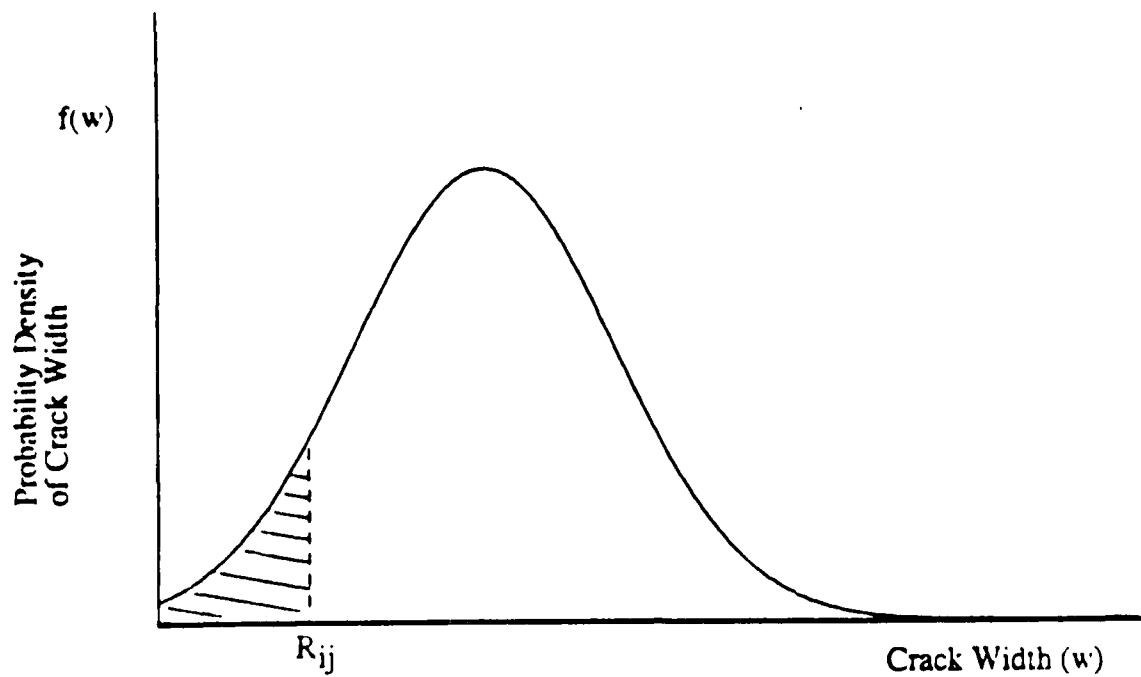
$\epsilon_{f,jk}$ = field of view limitation for distress type j at time i for system k

$\epsilon_{i,jk}$ = imaging limitation for distress type j at time i for system k

In this evaluation, only pavement cracking was evaluated. The types of cracking used were longitudinal and transverse cracking.

3.3.1 Resolution Error

Resolution is defined as the minimum distress size that can be picked up by an imaging technology. In the technologies evaluated, this represents the minimum crack width detectable. The probability of not observing detail due to resolution limitations is defined as the complement of the reliability of a technology. This concept is demonstrated below. Reliability is a quality measure and has a variety of meanings depending on the particular situation [12]. For example, it may be the expected fraction of time that an instrument or technology measures correctly, or it may be the probability that a technology measures correctly for a certain period of time.

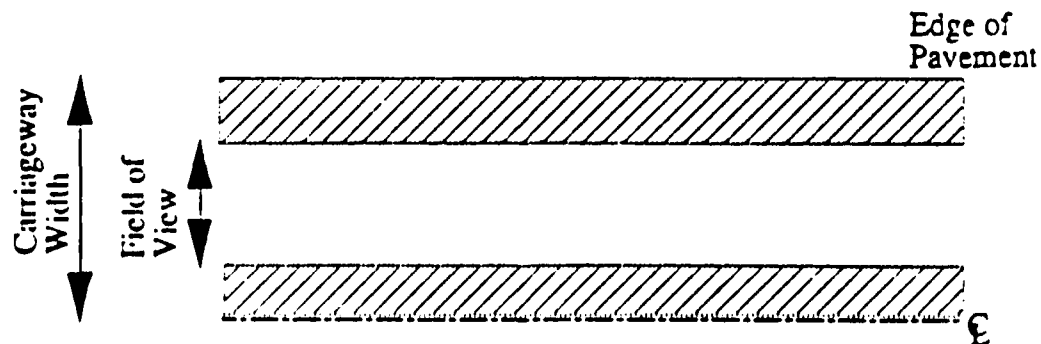


- R_{ij} = resolution of system k for distress j
- shaded portion is reliability with respect to resolution

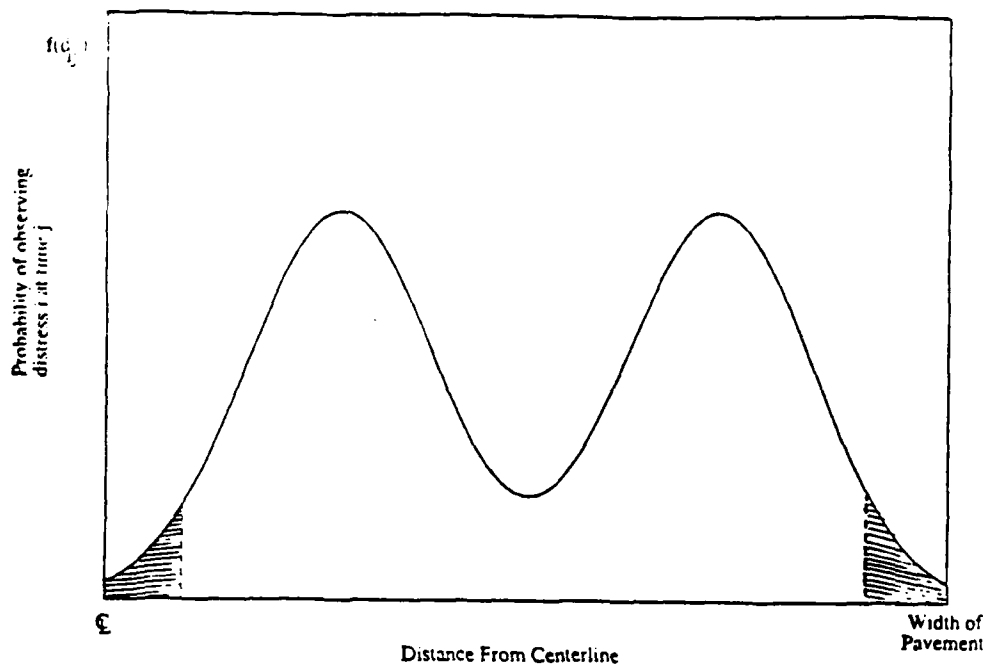
The expected value of the area of cracks on a pavement not observed due to resolution limitations was used as a measure of resolution error.

3.3.2 Field of View Limitation

The error due to field of view limitation was defined as shown below:



The area not viewed by a technology is represented by the hatched part of the figure. The probability of a distress being present in this unobserved area was used as a measure of the reliability of a technology in picking up distresses. This concept is demonstrated below.



- $d_{ij} = 1$ if distress i is present at time j
 $= 0$ otherwise
- shaded portion is reliability with respect to field of view

The expected area of cracks that are unobserved on a pavement due to field of view limitations was used as a measure of field of view error. This is computed from the expected number, expected width and expected length of cracks unobserved.

3.3.3 Imaging Limitations

Imaging limitation can be expressed as the complement of the observed area, such as the number of frames per unit length observed. The total area observed by a system can be defined as:

Total area observed = frame size * number of frames

The expected area of distresses not observed due to imaging limitation was used as a measure of imaging limitation error.

4 Error Assessment

4.1 Data Description

The actual data used to evaluate automated technologies were simulated pavement distresses and simulated data using two technologies for collection. Distributions and parameters used in the simulation of pavement distress were derived from two types of visual inspections. The first inspection was the evaluation of a 25 ft. x 60 ft. parking lot by a 9 person team. This evaluation consisted of an estimation of the extent of areas cracked using the methods used to estimate the PCI [8]. The results are given in Table 4.1. A second inspection was the accurate measurement of 50 randomly selected longitudinal and transverse cracks by a 5 person team. The measurement included crack widths at three locations along the crack and the length of the crack. The results are given in Table 4.2. These inspections are referred to as technology 1 and technology 2, respectively.

The results of technology 1 and 2 measurements were used to estimate the distribution of crack width, distribution of crack length, relationship between crack severity (width) and extent (length), and the distribution of the orientation of cracks.

It was not possible to separate the field of view and imaging limitation errors. Therefore, these were thus evaluated together. Simulation was carried out for each technology, to evaluate resolution error (ϵ_{njk}) and imaging system error ($\epsilon_{sjk} + \epsilon_{ijk}$).

4.1.1 Crack Length Distribution and Number of Cracks

The cracks in Table 4.2 were used to determine the average crack length. This was estimated to be 65 inches (5.418 feet). The average number of cracks on the segment was estimated from

$$\hat{N} = \frac{E(L_{tot})}{E(L_i)}$$

Table 4.1 Condition Evaluation by Technology 1

DISTRESS	SEVERITY	MEASUREMENTS (sq.ft.)								
		1	2	3	4	5	6	7	8	9
1. Alligator Cracks	L		450	720	351			49	4	574
	M	188		360	44	640	700	527	3	128
	H		32					13		
2. Block Cracks	L	106	240	250			320	74	44	
	M					405				
	H									
3. Transverse Longitudinal Cracks	L	91	110	21	112			43	8	29
	M			15				78	37	
	H									
4. Patch/Utility Cut	L	624	342	315	424	300	405	23	333	395
	M		81	115		155	14	31		
	H			2						
5. Potholes	L	3	5	4	2		1	2	3	2
	M					9			2	
	H								2	
6. Rutting	L		134	10						
	M		9							40
	H	6								
PCI		40	18	18	19	16	35	23	48	20

Average PCI = 26.3 - Poor
Standard Deviation = 11

II. PSI	1	2	3	4	5	6	7	8	9
Length of cracking (ft.)	196	481	887	263	697	680	360	29	468

Average Length = 451 feet

TABLE 4.2 Condition Evaluation by Technology 2.

LENGTH (in)	WIDTH VALUES (in.)			E(W)
	W1	W2	W3	
40	0.2	0.1	0.42	0.24
51	0.18	0.12	0.05	0.12
35	0.03	0.08	0.1	0.07
54	0.12	0.09	0.05	0.09
140	0.4	0.78	0.98	0.72
154	0.3	0.5	0.65	0.48
24	0.14	0.08	0.08	0.1
39	0.34	0.13	0.1	0.19
43	0.2	0.1	0.18	0.16
61	0.12	0.31	0.18	0.20
32	0.12	0.13	0.19	0.145
31	0.27	0.28	0.22	0.26
18	0.49	0.3	0.1	0.30
126	0.19	0.23	0.24	0.22
102	0.18	0.35	0.28	0.27
132	0.33	0.4	0.29	0.34
24	0.34	0.4	0.16	0.3
51	0.28	0.29	0.22	0.26
96	0.2	0.31	0.2	0.24
26	0.35	0.46	0.44	0.42
180	0.21	0.18	0.14	0.18
60	0.17	0.34	0.16	0.22
42	0.2	0.25	0.27	0.24
42	0.14	0.21	0.25	0.2
30	0.3	0.3	0.17	0.26
40	0.16	0.24	0.25	0.22
68	0.26	0.2	0.2	0.22
60	0.22	0.27	0.25	0.25
18	0.15	0.2	0.26	0.20
30	0.22	0.26	0.3	0.26
118	0.16	0.07	0.09	0.11
38	0.28	0.16	0.22	0.22
31	0.16	0.13	0.13	0.14
63	0.15	0.09	0.09	0.11
56	0.28	0.13	0.19	0.2
15.5	0.19	0.11	0.03	0.11
9	0.13	0.17	0.14	0.15
10	0.13	0.15	0.12	0.13
34	0.11	0.08	0.15	0.11
45	0.09	0.18	0.24	0.17
46.5	0.11	0.22	0.05	0.13
41	0.12	0.25	0.1	0.16
47.2	0.17	0.37	0.12	0.22
68.2	0.1	0.27	0.07	0.15
89	0.12	0.3	0.15	0.19
27.5	0.07	0.11	0.07	0.08

205	0.15	0.4	0.15	0.23
310	0.2	0.42	0.18	0.27
81	0.2	0.25	0.1	0.18
73	0.12	0.2	0.05	0.12

where:

\hat{N} = total number of cracks on the segment

$E(L_{tot})$ = Average total length of cracking on the segment (averaged over the nine observations by technology 1)

$E(L_i)$ = Average length of an individual crack on the segment (averaged over fifty observations by technology 2).

$$\hat{N} = \frac{451}{5.418} = 83 \text{ cracks}$$

The crack lengths were assumed to be normally distributed, and 83 crack lengths were randomly generated from a normal distribution with a mean of 65 inches. The results are given in Table 4.3. A comparison of the actual crack lengths (50 cracks from Technology 2) to the simulated ones from a normal distribution is given in Figure 4.1. The simulations fitted the actual data very well.

4.1.2 Crack Width Distribution

The distribution of crack widths for a pavement section is necessary to estimate the reliability of a technology with respect to resolution, and the resolution error of a technology.

The occurrence of cracks has been suggested to be modeled by a Poisson process by other researchers [13]. The Poisson event in this study was defined as the number of occurrences of cracks with width intervals of 1/10th of an inch. This value was used as it was found to be the lowest possible resolvable value of cracks width from optically collected data, currently in use. The crack width data given in Table 4.2 exhibited a Poisson distribution with a mean of 0.211 inches. This distribution was fitted and tested for goodness of fit. It was accepted at 95% confidence level. The observed and fitted values are shown in Figure 4.2.

Figure 4.1
COMPARISON OF ACTUAL TO SIMULATED
CRACK LENGTHS

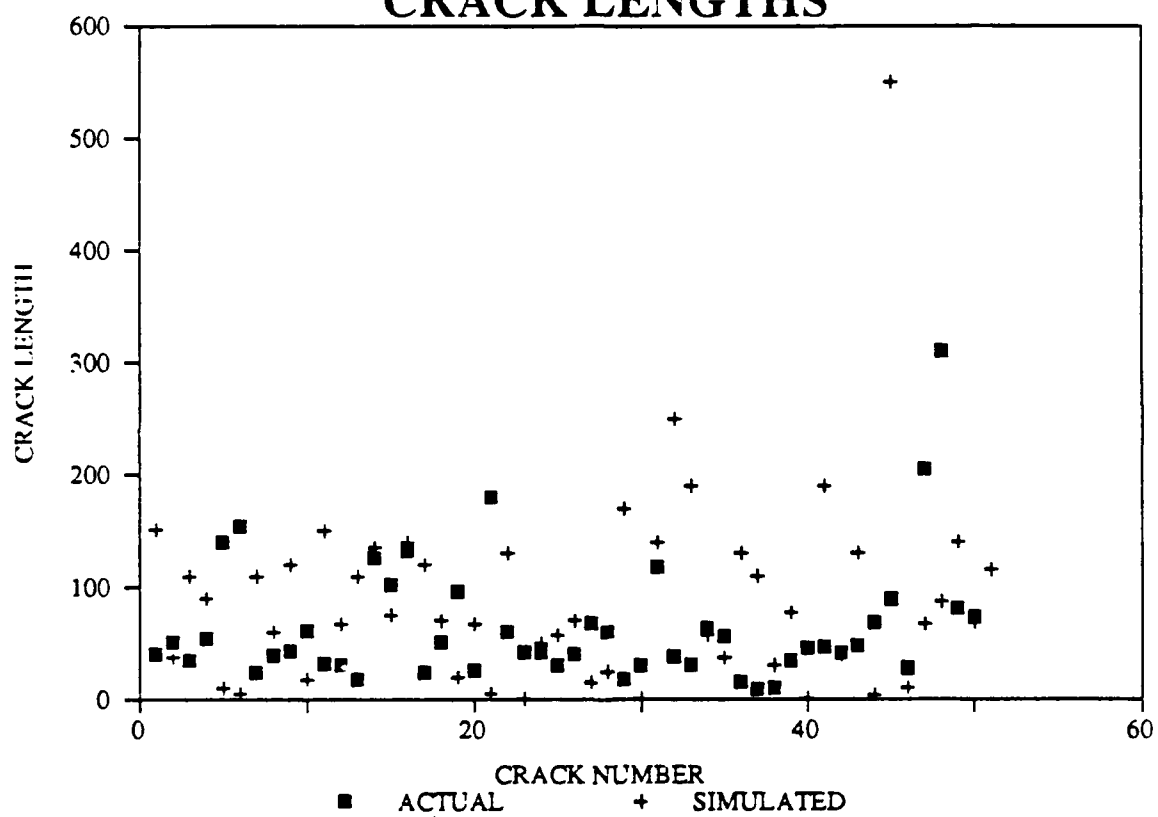
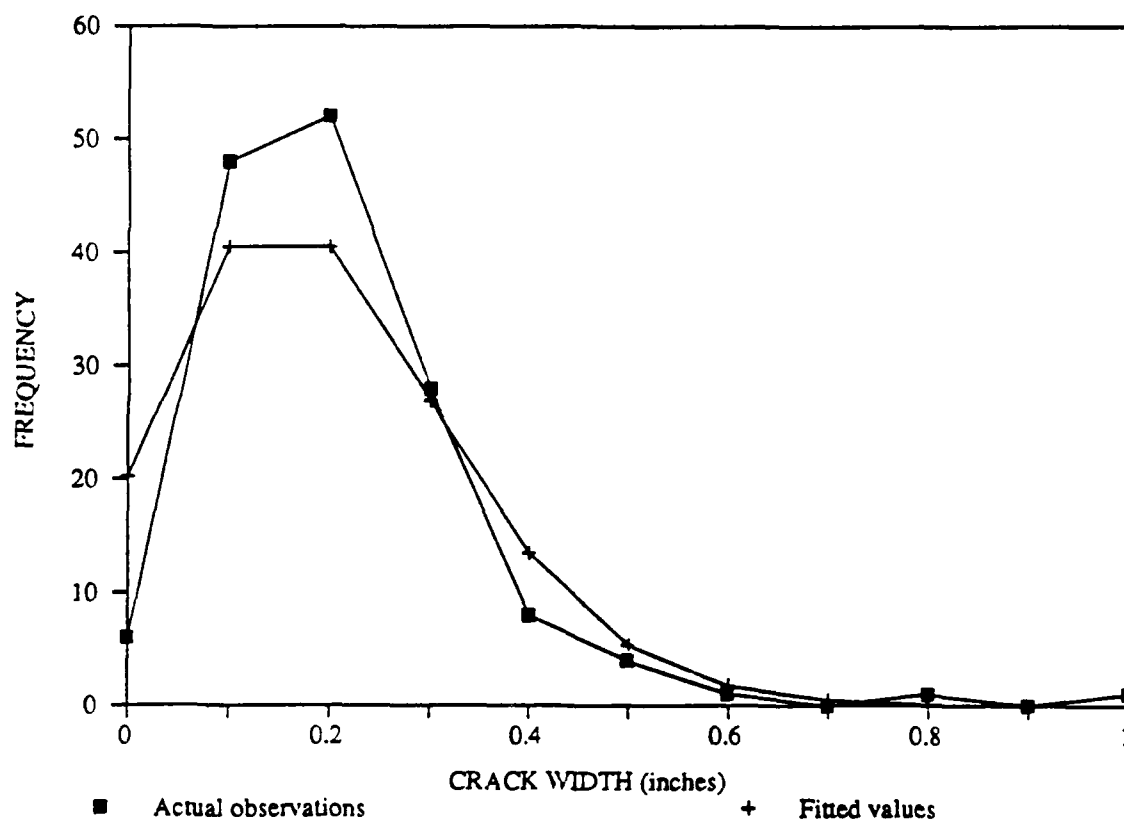


Figure 4.2
FITTED DISTRIBUTION OF CRACK WIDTH



The Poisson distribution is also a good discrete approximation of the gamma distribution. The gamma distribution was found to be a good fit to mapping error in subsurface sea profiling [14]. Based on these results crack widths were randomly generated from a Poisson distribution with a mean of 0.211 inches. The simulated cracks are given in Table 4.3.

4.1.3 Relationship Between Crack Length and Crack Width

The relationship between crack severity (width) and extent (length) was investigated. This relationship is shown in Figure 4.3 for the actual data. In the actual data, crack observations are clustered in the narrow crack range. This is particular to the pavement section observed, because it is at a lower level of distress. A section with more distress could exhibit a wider range of crack width and lengths. Figure 4.3 shows an upward trend, which means that as crack extents progress the cracks get wider. The relationship in Figure 4.3 may change with time, perhaps levelling off to a constant distribution.

Intuitively, these results can be used to test the following hypotheses:

- H_1 : resolution error becomes less important as cracking progresses.
- H_2 : field of view and imaging limitation error increases as cracking progresses, but tapers off to a constant level after some time or level of distress.

These hypotheses could be examined if time series data was available.

4.1.4 Crack Orientation

Cracks on a pavement segment appear in various orientations, such as transverse, longitudinal, or diagonal. The orientation of a crack affects its detectability if the technology used has field of view limitations. It is, therefore, useful to investigate the effect of crack orientation on measurement accuracy for various technologies. The data collected by technology

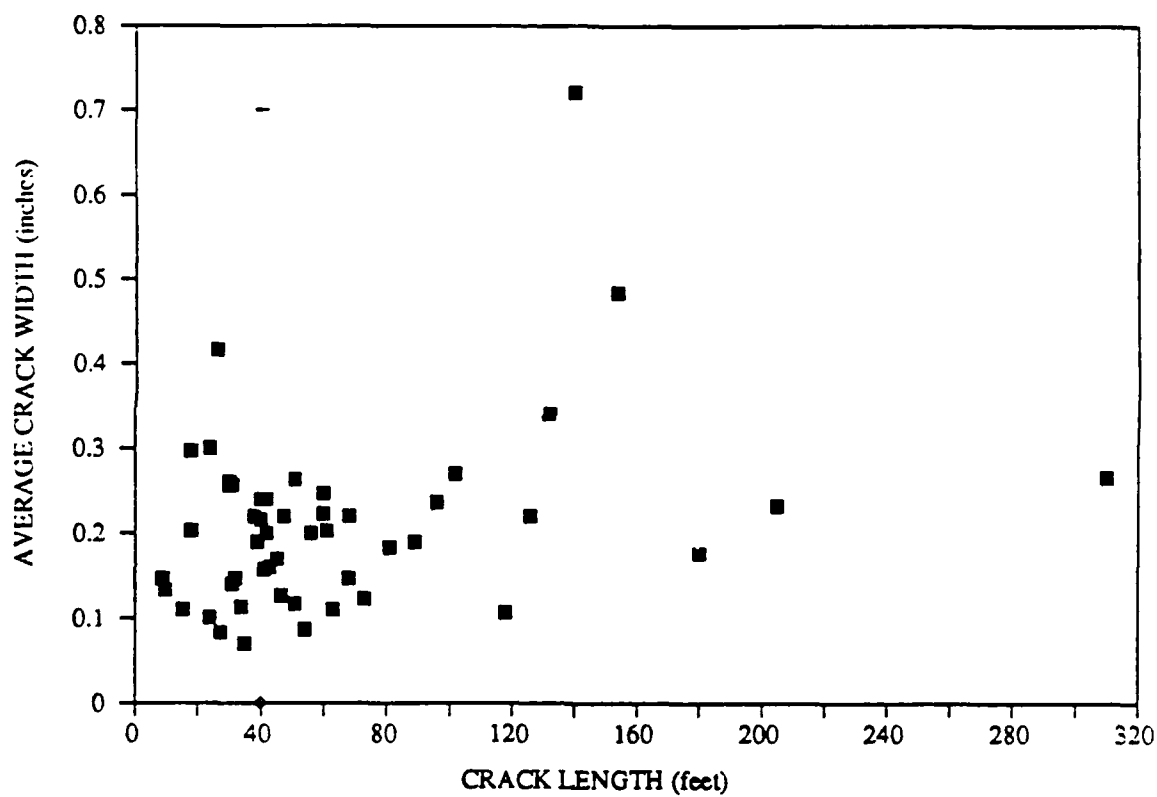
TABLE 4.3
DATA SET GENERATED FROM DISTRIBUTIONS OF CRACK LENGTH,
WIDTH AND ORIENTATION

CRACK NUMBER	SIMULATED LENGTH INS	SIMULATED WIDTH INS	ORIENTATION ¹	AREA OF CRACKING SQ IN
1	151	0.08	0	12.08
2	37.5	0.375	0	14.06
3	110	0.275	1	30.25
4	90	0.06	1	5.4
5	10	0.375	0	3.75
6	5	0.285	0	1.43
7	110	0.33	1	36.3
8	60	0.5	1	30
9	120	0.565	0	67.8
10	18	0.215	1	3.87
11	150	0.405	0	60.75
12	67	0.19	0	12.73
13	110	0.22	0	24.2
14	135	0.17	0	22.95
15	75	0.195	0	14.63
16	140	0.445	0	62.3
17	120	0	0	0
18	70	0.005	0	0.35
19	20	0.42	0	8.4
20	67	0.045	0	3.02
21	5	0.01	0	0.05
22	130	0.285	0	37.05
23	1	0.265	0	0.27
24	50	0.45	0	22.5
25	57	0	0	0
26	70	0.33	0	23.1
27	15	0.555	0	8.33
28	25	0.165	0	4.13
29	170	0.04	0	6.8
30	1	0.26	0	0.26
31	140	0	1	0
32	250	0.185	0	46.25
33	190	0.01	0	1.9
34	57	0.011	0	0.63
35	37	0.39	0	14.43
36	130	0.04	1	5.2
37	110	0	0	0
38	30	0.055	0	1.65
39	77	0.275	0	21.18

1 LEGEND: 1 - LONGITUDINAL CRACK
2 - TRANSVERSE CRACK

40	1	0.42	1	0.42
41	190	0.225	0	42.75
42	39	0.17	1	6.63
43	130	0.125	0	16.25
44	4	0.185	0	0.74
45	550	0.155	1	85.25
46	10	0.045	0	0.45
47	67	0.245	0	16.42
48	87	0.055	1	4.79
49	140	0.19	0	26.6
50	68	0.08	0	5.44
51	115	0.255	0	29.33
52	95	0	1	0
53	120	0.05	0	6
54	30	0.095	0	2.85
55	55	0.59	1	32.45
56	94	0.11	0	10.34
57	56	0.045	0	2.52
58	18	0.315	1	5.67
59	300	0.145	1	43.5
60	38	0.105	0	3.99
61	18	0	0	0
62	240	0.085	1	20.4
63	135	0.3	0	40.5
64	50	0.225	0	11.25
65	28	0.185	1	5.18
66	5	0.24	0	1.2
67	80	0.155	0	12.4
68	200	0.13	0	26
69	220	0.195	1	42.9
70	330	0	0	0
71	81	0.21	0	17.01
72	80	0.355	1	28.4
73	25	0.405	0	10.125
74	3	0	0	0
75	150	0.005	1	0.75
76	80	0.085	1	6.8
77	120	0.045	0	5.4
78	168	0.045	0	7.56
79	61	0.09	1	5.49
80	85	0.015	0	1.28
81	25	0.075	1	1.88
82	46	0	0	0
83	90	0.105	1	9.45
TOTALS	7737.5		Area Observed	1204.304

Figure 4.3
CRACK WIDTH VS CRACK LENGTH



2 was found to have a mix of 30% longitudinal cracks to 70% transverse cracks. This distribution was used to generate simulated data in Table 4.3 to evaluate the accuracy of different technologies including sensitivity of the measurement error with respect to crack orientation.

4.2 Technologies Evaluated

The technologies evaluated are classified as technology 3 and technology 4. Technology 3 is a high resolution camera with limited field of view and imaging capabilities. This technology misses cracks with widths less than 0.05 in. It also has a field of view and imaging limitation as defined in Figure 4.4. Technology 4 is a video camera with a resolution of 0.34 in. This technology misses cracks with widths less than 0.34 in., but has no field of view or imaging limitation. The area viewed by each of the technologies is graphically depicted in Figure 4.4.

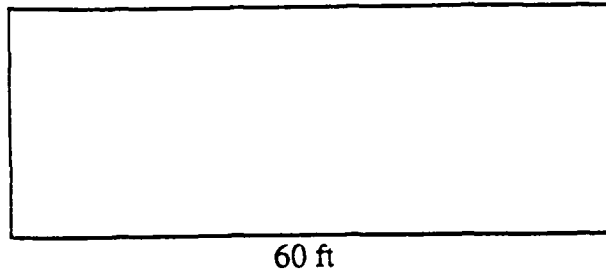
4.3 Results

4.3.1 Resolution Error

Resolution errors for a typical pavement segment were computed for technologies 3 and 4. This was done by estimating the percentage area of cracking unobserved due to resolution limitations. The percentage area of cracking unobserved was predicted using the value of crack width simulated randomly from a Poisson distribution, and the crack lengths simulated from a normal distribution. The proportions of cracked areas observed by technologies 3 and 4 are given in Table 4.4 and graphically depicted in Figure 4.5.

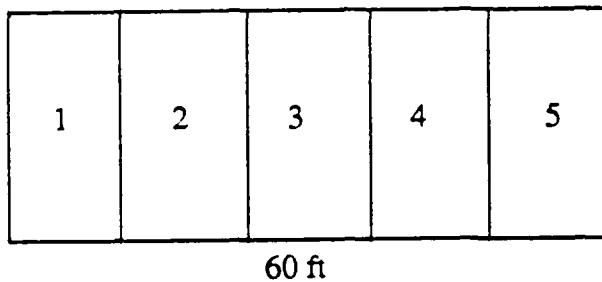
The resolution error for technology 3 is almost negligible. This can be seen in Figure 4.5, where there are no points on the actual area cracked axis. The resolution error for technology 4 is quite significant. This can be seen as all the points in Figure 4.5. plotting on the actual area cracked axis. However, technology 4 measures very accurately the areas cracked when crack widths are greater than the resolution. This will be discussed in the following section.

1. TECHNOLOGY 1
Visual Inspection, Aggregate Index



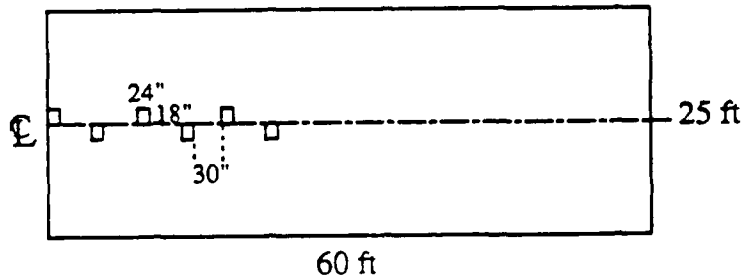
- Total area observed
- Resolution .25 in

2. TECHNOLOGY 2
Visual Inspection, Random Sample



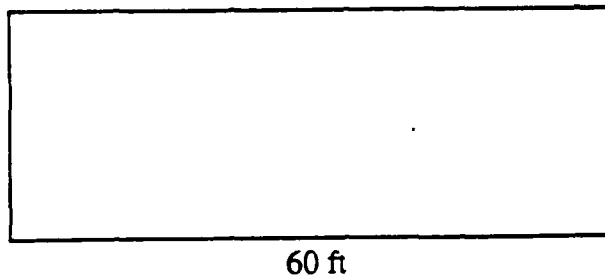
- 10 cracks observed for each section
- Resolution 0.001 in

3. TECHNOLOGY 3
High Resolution Camera



- Staggered images
- Resolution 0.05 in

4. TECHNOLOGY 4
Video Camera



- Total area observed
- Resolution 0.34 in

Figure 4.4 Inspection Technologies

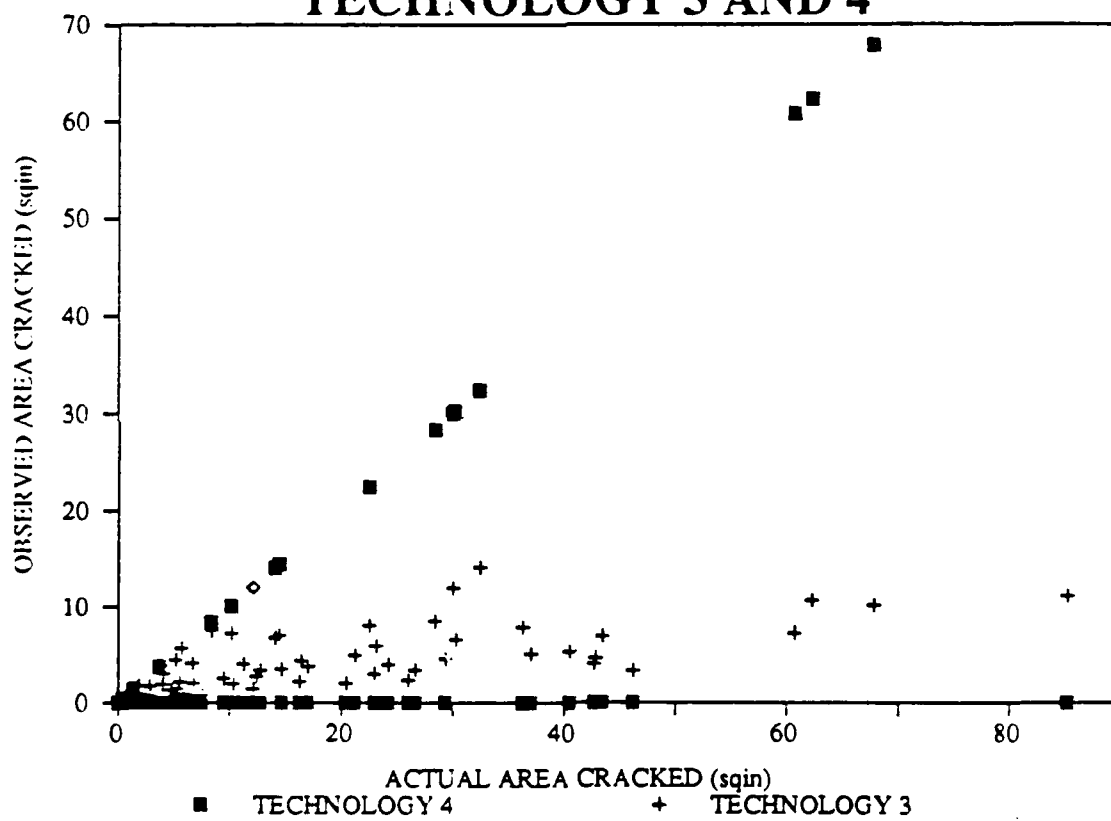
TABLE 4.4
COMPARISON OF AREAS OBSERVED BY
TECHNOLOGIES 3 AND 4

CRACK NUMBER	AREA OF CRACKING SQ INS	AREA OBSERVED	
		TECH 4	TECH 3
1	12.08	0.00	1.44
2	14.06	14.06	6.75
3	30.25	30.25	6.60
4	5.4	0.00	1.44
5	3.75	3.75	3.75
6	1.43	1.43	1.43
7	36.3	0.00	7.92
8	30	30.00	12.00
9	67.8	67.80	10.17
10	3.87	0.00	3.87
11	60.75	60.75	7.29
12	12.73	0.00	3.42
13	24.2	0.00	3.96
14	22.95	0.00	3.06
15	14.63	0.00	3.51
16	62.3	62.30	10.68
17	0	0.00	0.00
18	0.35	0.00	0.00
19	8.4	8.40	7.56
20	3.02	0.00	0.81
21	0.05	0.00	0.05
22	37.05	0.00	5.13
23	0.27	0.00	0.27
24	22.5	22.50	8.10
25	0	0.00	0.00
26	23.1	0.00	5.94
27	8.33	8.32	8.33
28	4.13	0.00	2.97
29	6.8	0.00	0.72
30	0.26	0.00	0.26
31	0	0.00	0.00
32	46.25	0.00	3.33
33	1.9	0.00	0.18
34	0.63	0.00	0.20
35	14.43	14.43	7.02
36	5.2	0.00	0.96
37	0	0.00	0.00
38	1.65	0.00	0.99
39	21.18	0.00	4.95
40	0.42	0.42	0.42
41	42.75	0.00	4.05
42	6.63	0.00	4.08
43	16.25	0.00	2.25
44	0.74	0.00	0.74
45	85.25	0.00	11.16

46	0.45	0.00	0.45
47	16.42	0.00	4.41
48	4.79	0.00	1.32
49	26.6	0.00	3.42
50	5.44	0.00	1.44
51	29.33	0.00	4.59
52	0	0.00	0.00
53	6	0.00	0.90
54	2.85	0.00	1.71
55	32.45	32.45	14.16
56	10.34	0.00	1.98
57	2.52	0.00	0.81
58	5.67	0.00	5.67
59	43.5	0.00	6.96
60	3.99	0.00	1.89
61	0	0.00	0.00
62	20.4	0.00	2.04
63	40.5	0.00	5.40
64	11.25	0.00	4.05
65	5.18	0.00	4.44
66	1.2	0.00	1.20
67	12.4	0.00	2.79
68	26	0.00	2.34
69	42.9	0.00	4.68
70	0	0.00	0.00
71	17.01	0.00	3.78
72	28.4	28.40	8.52
73	10.13	10.13	7.29
74	0	0.00	0.00
75	0.75	0.00	0.12
76	6.8	0.00	2.04
77	5.4	0.00	0.81
78	7.56	0.00	0.81
79	5.49	0.00	2.16
80	1.28	0.00	0.27
81	1.88	0.00	1.80
82	0	0.00	0.00
83	9.45	0.00	2.52

AREA	1204.304	395.39	274.51
OBSERVED			
PERCENTAGE		32.83	22.79
AREA			

Figure 4.5
AREA OF CRACKING OBSERVED BY
TECHNOLOGY 3 AND 4



The reliability with respect to resolution is much higher for technology 3 than technology 4 over the entire pavement segment.

4.3.2 Imaging System Error

Imaging system errors were calculated for technology 3 as technology 4 does not have a field of view or imaging limitation. The distribution of this error type across each crack length observed was investigated. This distribution was also tested for its sensitivity to crack type distribution. Five different distributions of crack type were used

- all longitudinal
- all transverse
- 70% longitudinal, 30% transverse
- 50% longitudinal, 50% transverse
- 30% longitudinal, 70% transverse

The results are given in Tables 4.5 through 4.7, and graphically depicted in Figures 4.6 and 4.7. The ranges of this error for each crack observed can be seen in Tables 4.5 and 4.6. The error calculated is the minimum error as the simulations assume that all cracks fall within frames and each crack completely transverses the frame as follows:

TABLE 4.5
EFFECT OF CRACK ORIENTATION ON ACCURACY OF OBSERVATIONS BY
TECHNOLOGY 3

CRACK NUMBER	FIELD OF VIEW AND IMAGING LIMITATION				
	1.0/0.0	Ratio of Transverse to Longitudinal Cracks			
		0.0/1.0	0.3/0.7	0.5/0.5	0.7/0.3
1	0.88	0.84	0.87	0.86	0.87
2	0.52	0.36	0.47	0.44	0.47
3	0.84	0.78	0.82	0.81	0.82
4	0.80	0.73	0.78	0.77	0.78
5	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00
7	0.84	0.78	0.82	0.81	0.82
8	0.70	0.60	0.67	0.65	0.67
9	0.85	0.80	0.84	0.83	0.84
10	0.00	0.00	0.00	0.00	0.00
11	0.88	0.84	0.87	0.86	0.87
12	0.73	0.64	0.70	0.69	0.70
13	0.84	0.00	0.59	0.42	0.59
14	0.87	0.82	0.85	0.84	0.85
15	0.76	0.68	0.74	0.72	0.74
16	0.87	0.83	0.86	0.85	0.86
17	0.85	0.80	0.84	0.83	0.84
18	0.74	0.66	0.72	0.70	0.72
19	0.10	0.00	0.07	0.05	0.07
20	0.73	0.64	0.70	0.69	0.70
21	0.00	0.00	0.00	0.00	0.00
22	0.86	0.82	0.85	0.84	0.85
23	0.00	0.00	0.00	0.00	0.00
24	0.64	0.52	0.60	0.58	0.60
25	0.68	0.58	0.65	0.63	0.65
26	0.74	0.66	0.72	0.70	0.72
27	0.00	0.00	0.00	0.00	0.00
28	0.28	0.04	0.21	0.16	0.21
29	0.89	0.00	0.63	0.45	0.63
30	0.00	0.00	0.00	0.00	0.00
31	0.87	0.83	0.86	0.85	0.86
32	0.93	0.90	0.92	0.92	0.92
33	0.91	0.87	0.90	0.89	0.90
34	0.68	0.58	0.65	0.63	0.65
35	0.51	0.35	0.46	0.43	0.46
36	0.00	0.00	0.00	0.00	0.00
37	0.00	0.00	0.00	0.00	0.00
38	0.00	0.00	0.00	0.00	0.00
39	0.77	0.69	0.74	0.73	0.74
40	0.00	0.00	0.00	0.00	0.00
41	0.91	0.87	0.90	0.89	0.90
42	0.54	0.38	0.49	0.46	0.49
43	0.86	0.82	0.85	0.84	0.85
44	0.00	0.00	0.00	0.00	0.00
45	0.97	0.87	0.94	0.92	0.94

46	0.00	0.00	0.00	0.00	0.00
47	0.73	0.64	0.70	0.69	0.70
48	0.79	0.72	0.77	0.76	0.77
49	0.87	0.83	0.86	0.85	0.86
50	0.74	0.65	0.71	0.69	0.71
51	0.84	0.79	0.83	0.82	0.83
52	0.81	0.75	0.79	0.78	0.79
53	0.85	0.80	0.84	0.83	0.84
54	0.40	0.20	0.34	0.30	0.34
55	0.67	0.56	0.64	0.62	0.64
56	0.81	0.74	0.79	0.78	0.79
57	0.68	0.57	0.65	0.63	0.65
58	0.00	0.00	0.00	0.00	0.00
59	0.94	0.84	0.91	0.89	0.91
60	0.53	0.37	0.48	0.45	0.48
61	0.00	0.00	0.00	0.00	0.00
62	0.93	0.90	0.92	0.91	0.92
63	0.87	0.82	0.85	0.84	0.85
64	0.64	0.52	0.60	0.58	0.60
65	0.36	0.14	0.29	0.25	0.29
66	0.00	0.00	0.00	0.00	0.00
67	0.78	0.70	0.75	0.74	0.75
68	0.91	0.88	0.90	0.90	0.90
69	0.92	0.89	0.91	0.90	0.91
70	0.95	0.93	0.94	0.94	0.94
71	0.78	0.70	0.76	0.74	0.76
72	0.78	0.70	0.75	0.74	0.75
73	0.28	0.04	0.21	0.16	0.21
74	0.00	0.00	0.00	0.00	0.00
75	0.88	0.84	0.87	0.86	0.87
76	0.78	0.70	0.75	0.74	0.75
77	0.85	0.80	0.84	0.83	0.84
78	0.89	0.86	0.88	0.88	0.88
79	0.70	0.61	0.68	0.66	0.68
80	0.79	0.72	0.77	0.75	0.77
81	0.28	0.04	0.21	0.16	0.21
82	0.61	0.48	0.57	0.54	0.57
83	0.80	0.73	0.78	0.77	0.78

TABLE 4.6
STATISTICS OF FIELD OF VIEW AND IMAGING ERROR:
TECHNOLOGY 3

Expected value of error		
Mixed (0.3/0.7)	0.567	
Transverse (1.0/0.0)	0.593	
Longitudinal (0.0/1.0)	0.507	
Standard deviation of error		
Mixed (0.3/0.7)	0.337	
Transverse (1.0/0.0)	0.342	
Longitudinal (0.0/1.0)	0.344	
Average crack length	93.223	inches
Standard deviation of		
crack length	85.316	inches
Total length of cracks	7737.5	inches
	644.792	feet

TABLE 4.7
FREQUENCY DISTRIBUTION OF FIELD OF VIEW AND IMAGING
ERROR

Midpoint of Crack Width Range	Ratio of Transverse to Longitudinal Cracks				
	1.0/0.0	0.0/1.0	0.7/0.3	0.5/0.5	0.3/0.7
0	17	20	17	17	17
0.1	1	3	1	1	1
0.2	0	2	0	3	0
0.3	3	0	4	2	4
0.4	2	4	1	0	1
0.5	0	1	4	6	4
0.6	4	7	2	3	2
0.7	8	12	9	12	9
0.8	17	14	18	12	18
0.9	22	18	20	22	20
1	9	2	7	5	7

Figure 4.6
EFFECT OF CRACK ORIENTATION

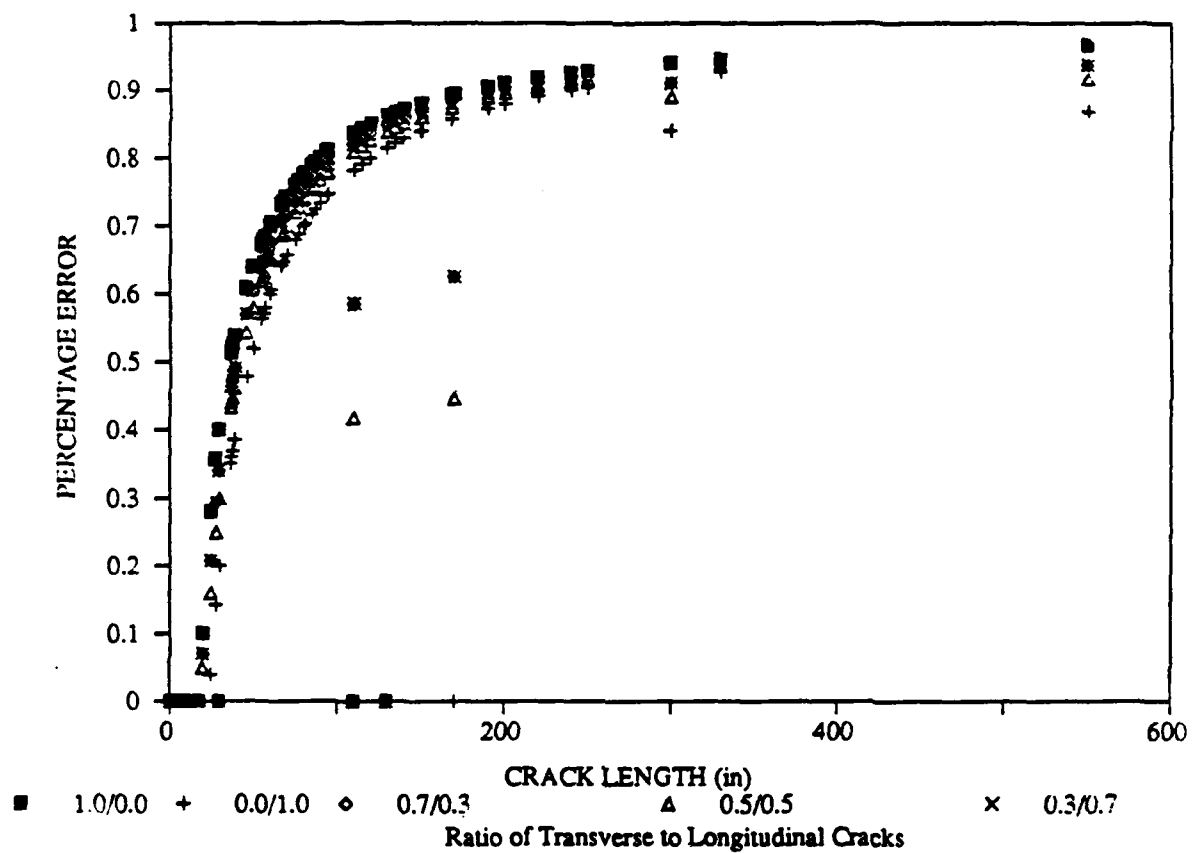
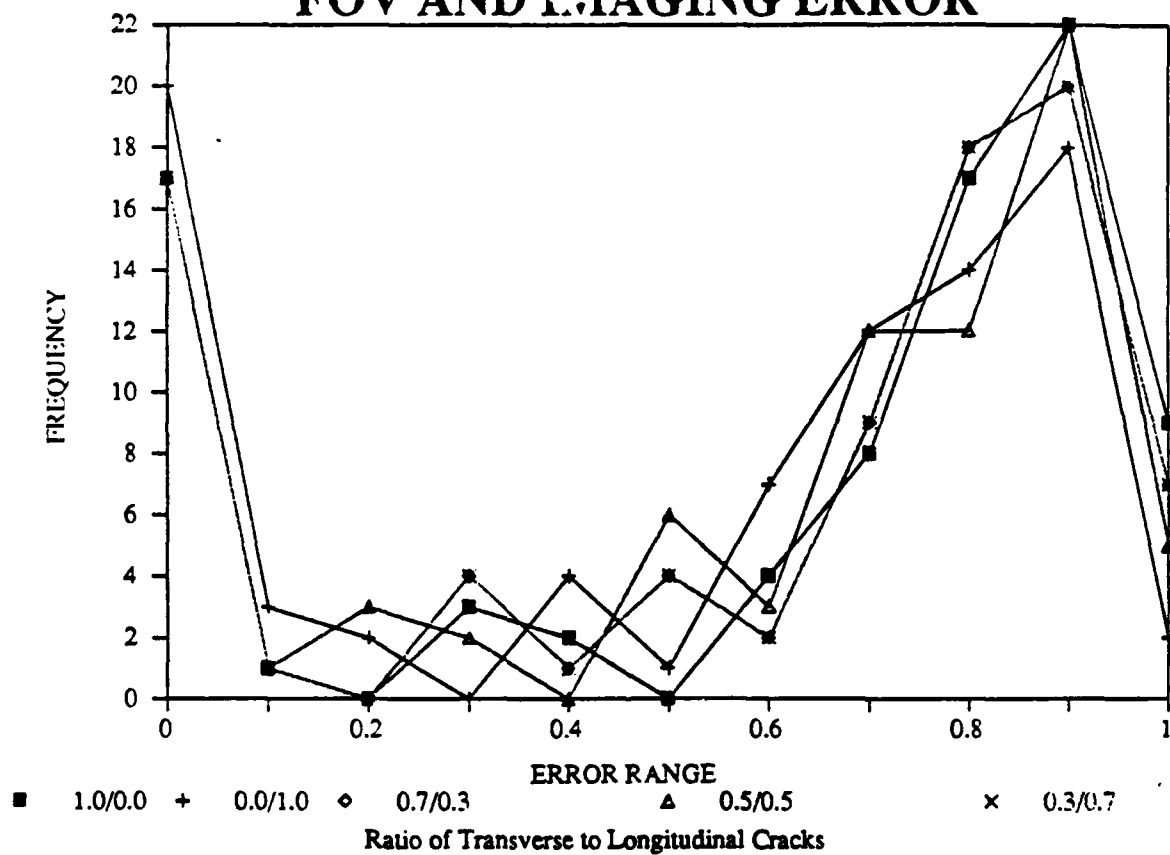
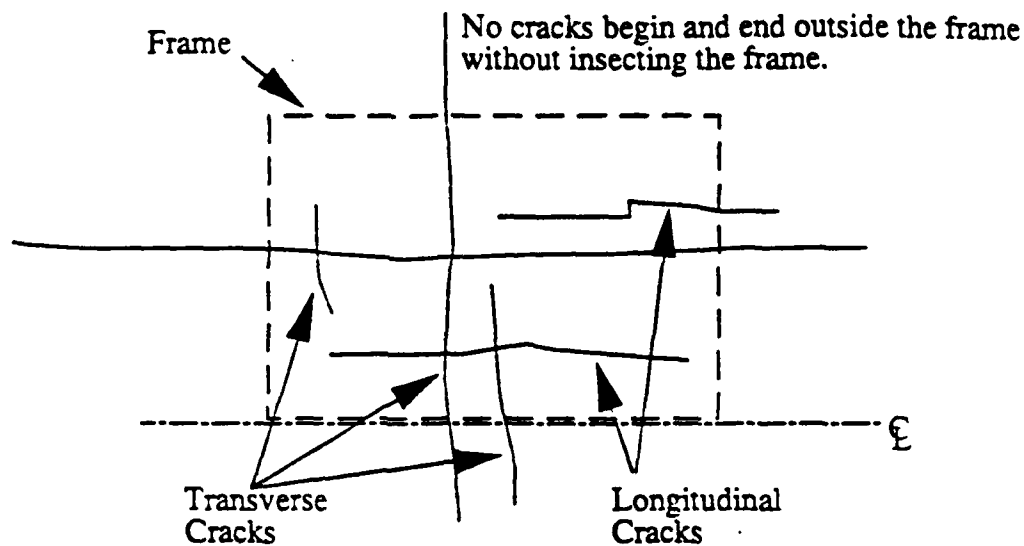


Figure 4.7
**FREQUENCY DISTRIBUTION OF
 FOV AND IMAGING ERROR**





The estimated errors are shown in Table 4.5.

Table 4.6 shows the statistics associated with the errors. The expected values of the error are lowest when there are more longitudinal cracks, and higher when there are more transverse cracks. The standard deviation of the error, however, seems to be independent of orientation. Technology 3, therefore, performs better for pavement sections with more longitudinal cracking than transverse cracking but is equally precise for all types of crack orientation. This precision can be seen in Figure 4.6 where all the points follow the same general curve, regardless of orientation. Figure 4.6 also shows that the error increases with crack length, as expected.

The frequency distribution of the error due to field of view and imaging limitation is given in Table 4.7 for various mixes of crack orientation. This is graphically displayed in Figure 4.7. The distribution appears to be the same for all mixes of crack type. This result leads to the conclusion that the distribution of crack types or orientations does not have a significant effect on the imaging system error.

4.3.3 Error per Individual Crack

A comparison of the performance of technology 3 and 4 with respect to each crack observed was done. This type of analysis is useful in investigating technological limitations. The results are shown in Table 4.8 and graphically displayed in Figure 4.8. Technology 4 had an error of 0 or 100 percent with respect to an individual cracks. This is mainly due to its resolution limitation. If the resolution of this technology is increased slightly it will result in a great improvement in measurement accuracy. Technology 3 showed quite variable error statistics with respect to an individual crack. The measurement error was generally high, but declined as the extent of a distress increased. This indicates that significant improvement in measurement accuracy can be achieved by increasing the field of view capabilities of this technology.

5 Conclusions and Recommendations

The objectives of this paper were to identify the main sources of error in automated visual inspection systems, quantify these errors for a particular system design (technology), and select a measure of system accuracy. A survey of the technologies currently in use, and the concepts and approaches used in data collection for pavement surface distress were presented. Data representing actual distresses was simulated using parameters and distributions from data collected through visual inspection. Simulations of two automated technologies were used to generate observed distress data. The accuracy of the automated technologies was assessed by comparing the simulated actual distresses to the simulated observed distresses.

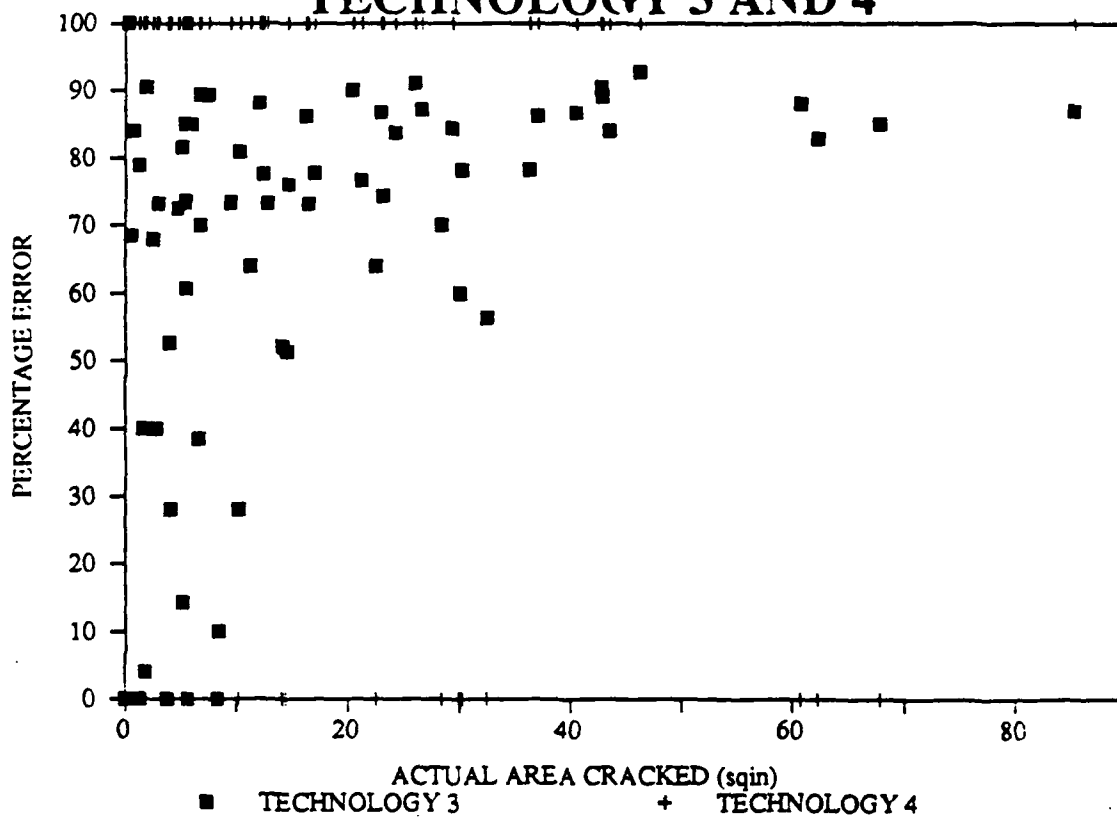
The analysis demonstrated the difficulties in the evaluation of a technology's performance, and the presence and magnitude of errors. In the selection of a measure of system accuracy, various possible measures can be used. In this paper two measures were developed, accuracy of a technology across an entire pavement section observed, and the accuracy per individual crack observed. These two measures can be used to make various management decisions. For

TABLE 4.8
ERROR PER INDIVIDUAL CRACK IN A SCENE

CRACK NUMBER	AREA OF CRACKING SQ INS	AREA OBSERVED		ERROR PER CRACK	
		TECH 4	TECH 3	TECH 4	TECH 3
1	12.08	0.00	1.44	100	88.08
2	14.06	14.06	6.75	0	52.00
3	30.25	30.25	6.60	0	78.18
4	5.4	0.00	1.44	100	73.33
5	3.75	3.75	3.75	0	0.00
6	1.43	1.43	1.42	0	0.35
7	36.3	0.00	7.92	100	78.18
8	30	30.00	12.00	0	60.00
9	67.8	67.80	1017.00	0	-1400.00
10	3.87	0.00	3.87	100	0.00
11	60.75	60.75	7.29	0	88.00
12	12.73	0.00	3.42	100	73.13
13	24.2	0.00	3.96	100	83.64
14	22.95	0.00	3.06	100	86.67
15	14.63	0.00	3.51	100	76.00
16	62.3	62.30	10.68	0	82.86
17	0	0.00	0.00	0	0.00
18	0.35	0.00	0.00	100	100.00
19	8.4	8.40	7.56	0	10.00
20	3.02	0.00	0.81	100	73.13
21	0.05	0.00	0.05	100	0.00
22	37.05	0.00	5.13	100	86.15
23	0.265	0.00	0.27	100	-1.89
24	22.5	22.50	8.10	0	64.00
25	0	0.00	0.00	0	0.00
26	23.1	0.00	5.94	100	74.29
27	8.33	8.32	8.33	0	-0.06
28	4.13	0.00	2.97	100	28.00
29	6.8	0.00	0.72	100	89.41
30	0.26	0.00	0.26	100	0.00
31	0	0.00	0.00	0	0.00
32	46.25	0.00	3.33	100	92.80
33	1.9	0.00	0.18	100	90.53
34	0.63	0.00	0.20	100	68.10
35	14.43	14.43	7.02	0	51.35
36	5.2	0.00	0.96	100	81.54
37	0	0.00	0.00	0	0.00
38	1.65	0.00	0.99	100	40.00
39	21.18	0.00	4.95	100	76.62
40	0.42	0.42	0.42	0	0.00
41	42.75	0.00	4.05	100	90.53
42	6.63	0.00	4.08	100	38.46
43	16.25	0.00	2.25	100	86.15
44	0.74	0.00	0.74	100	0.00
45	85.25	0.00	11.16	100	86.91

46	0.45	0.00	0.45	100	0.00
47	16.42	0.00	4.41	100	73.13
48	4.79	0.00	1.32	100	72.41
49	26.6	0.00	3.42	100	87.14
50	5.44	0.00	1.44	100	73.53
51	29.33	0.00	4.59	100	84.35
52	0	0.00	0.00	0	0.00
53	6	0.00	0.90	100	85.00
54	2.85	0.00	1.71	100	40.00
55	32.45	32.45	14.16	0	56.36
56	10.34	0.00	1.98	100	80.85
57	2.52	0.00	0.81	100	67.86
58	5.67	0.00	5.67	100	0.00
59	43.5	0.00	6.96	100	84.00
60	3.99	0.00	1.89	100	52.63
61	0	0.00	0.00	0	0.00
62	20.4	0.00	2.04	100	90.00
63	40.5	0.00	5.40	100	86.67
64	11.25	0.00	4.05	100	64.00
65	5.18	0.00	4.44	100	14.29
66	1.2	0.00	1.20	100	0.00
67	12.4	0.00	2.79	100	77.50
68	26	0.00	2.34	100	91.00
69	42.9	0.00	4.68	100	89.09
70	0	0.00	0.00	0	0.00
71	17.01	0.00	3.78	100	77.78
72	28.4	28.40	8.52	0	70.00
73	10.13	10.13	7.29	0	28.00
74	0	0.00	0.00	0	0.00
75	0.75	0.00	0.12	100	84.00
76	6.8	0.00	2.04	100	70.00
77	5.4	0.00	0.81	100	85.00
78	7.56	0.00	0.81	100	89.29
79	5.49	0.00	2.16	100	60.66
80	1.28	0.00	0.27	100	78.82
81	1.88	0.00	1.80	100	4.00
82	0	0.00	0.00	0	0.00
83	9.45	0.00	2.52	100	73.33

Figure 4.8
ERROR PER INDIVIDUAL CRACK FOR
TECHNOLOGY 3 AND 4



example, the aggregate measure can be used in the choice of a suitable technology given the level of distress on a pavement. The disaggregate error measure can be used to correct for technological limitations once a particular technology has been selected.

A number of crack attributes were found to affect the level of accuracy achieved by a given technology. Crack width was the main factor affecting technologies with low resolution capabilities. Crack length was a major factor affecting the accuracy of technologies with field of view or imaging limitations. The distribution of crack types (transverse vs. longitudinal cracks) had no significant impact on the accuracy of a technology. This information can be usefully applied in the development or refinement stage of technology configuration. For example, for a given technology, trade-offs between resolution and field of view can be made depending on the relation between crack sensitivity (width) and extent (length). One can also combine two currently existing technologies to get better data. For example, combining a low resolution video camera with no field of view or imaging limitations to collect cracking extent, with a high resolution camera with field of view and imaging limitations to collect crack width data.

This paper utilized a number of levels of aggregation error. The choice of the level of aggregation affects the type of data required for evaluation and the type of evaluation. For example, the accuracy of a technology with respect to an individual crack on a scene will require intensive data from a large sample of cracks. The aggregation of this accuracy across an entire frame, sampled section, sampled link, or pavement network requires some analysis. There is a need to conduct research in this area, specifically in the understanding of the various assumptions required for such an analysis, and methods of verifying them.

The probability distributions of actual cracking levels for this analysis were based on a sample from a single site. This limits the evaluation results and conclusions to be accurate with respect to this site only. Extension of this analysis for more general situations will require the development of new probability distributions from inventory data on the performance of the pavements being evaluated.

A number of factors affecting the accuracy of a technology were not evaluated in this paper. These include the effects of increased sampling rates on accuracy, the relation between frame size, resolution, field of vision, and imaging speed, and their relative effects on technology accuracy. In conclusion, this paper investigated methods of evaluating accuracy and performance of automated technologies. Assumptions were made to obtain analytically feasible results.

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